A Decision Support System for a Holistic Purchasing Process of Raw Materials

Joana Mourão Cruz Teixeira

Master's Dissertation

Supervisor: Prof. Manuel Augusto de Pina Marques

U.PORTO

FEUP FACULDADE DE ENGENHARIA UNIVERSIDADE DO PORTO

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Abstract

Players in the manufacturing industry are continuously pushed to reduce its operational costs in order to survive in a highly competitive global market. Under such demanding environment, purchasing processes have been playing a more central role than ever before, arising as a competitive weapon to foster company's profitability and also to enhance an effective inventory management.

The present work was motivated by the case of a portuguese metal packaging industry, whose lack of analytical support and disintegration amongst its several functional departments was leading to excessive raw material inventory levels and a sub optimal placement of purchasing orders. The goal comprises the development of a methodology spelled out in a Decision Support System to help the company conduct purchasing orders while maintaining the required holistic integration.

Despite the attention given by researchers towards replenishment policies and supplier selection, these two issues are often treated as solo acts, which prevents the achievement of an overall optimal solution. In this dissertation, a state-of-the-art replenishment policy is combined with a mathematical optimisation model to create purchasing orders that, given the suppliers conditions and company's cost structure, promote the best trade-off between acquisition and inventory costs. In an effort to integrate productive constraints and leverage stock throughout the manufacturing line, a complementary simulation model of the productive process is developed to attain a more reliable forecast of coil consumption. However, due to the need to adjust the provided manufacturing parameters to the case-by-case decisions of the planning department, this methodological step can only be fully assessed after its on-site implementation.

The application of the proposed methodology showcased expected savings of 4,2% in the sum of acquisition and carrying costs, and a potential reduction of 22% in terms of stock coverage. The results were achieved without harming the intended service level, which brought up an increased confidence that the methodology can be materialised in significant gains for the company. In fact, the project's goal was accomplished despite the integration of the company's overestimated forecast of coil consumption, leading us to believe that the actual outcomes can be even more promising when providing the intended unbiased forecast. Since the devised tool is being currently internalised, a subsequent measurement of the actual impacts of the end-to-end methodology can be conducted, allowing to confirm its expected outcomes.

Resumo

As empresas do setor industrial são continuamente pressionadas a reduzir os seus custos operacionais para sobreviverem num mercado global cada vez mais competitivo. Num meio tão exigente, os processos de compra têm vindo a desempenhar um papel cada vez mais crucial, sendo usados como uma vantagem competitiva para fomentar a rentabilidade das empresas e possibilitar uma gestão eficiente do seu inventário.

O presente trabalho teve como motivação o caso real de uma empresa portuguesa de embalagens metálicas, em que a falta de suporte analítico e a disconexão entre os diversos departamentos é responsável pela existência de níveis excessivos de inventário de matérias-primas e de um escalonamento de ordens de compra longe do ideal. O objetivo consiste no desenvolvimento de uma metodologia implementada num Sistema de Apoio à Decisão para auxiliar a empresa a definir as ordens de compra com a necessária integração holística.

Apesar da atenção dedicada pelos investigadores às políticas de reabastecimento e ao processo de seleção de fornecedores, estes dois problemas são geralmente tratados separadamente, o que impede a obtenção de uma solução ótima global. Nesta dissertação, uma política de reabastecimento de inventário *state-of-the-art* é aliada a um modelo de optimização matemático desenvolvido para criar ordens de compra que, dadas as limitações dos fornecedores e a própria estrutura de custos da empresa, promovem o melhor compromisso entre custos de aquisição e custos inventário. De forma a integrar restrições produtivas e tirar partido da existência de inventário ao longo da linha produtiva, foi desenvolvida uma simulação complementar do processo produtivo com o objetivo de obter uma previsão mais fiável do consumo de rolo de chapa. Contudo, devido à necessidade de ajustar os parâmetros de produção fornecidos às decisões pontuais do departamento de planeamento, este passo metodológico só pode ser deviadamente avaliado aquando da sua implementação.

A aplicação da metodologia proposta apresentou poupanças de 4,2% na soma dos custos de posse e aquisição, e uma redução potencial de 22% da cobertura total de *stock*. Os resultados foram atingidos sem afetarem o nível de serviço, o que gerou confiança de que a aplicação da metodologia seja materializada em ganhos significativos para a empresa. Refira-se ainda que o objetivo do projeto foi cumprido apesar da integração de uma previsão sobrestimada de consumo de rolo de chapa, levando a crer que os resultados finais sejam ainda mais promissores quando for fornecida a previsão não tendenciosa que se pretende. Uma vez que a ferramenta desonvolvida já começou a ser internalizada, será possível conduzir uma análise futura dos impactos reais de toda a metodologia, possibilitando a confirmação dos ganhos esperados.

Acknowledgments

Looking back at the beginning of my journey as an Engineering student, I still see myself writing a time capsule with my hopes and fears for the next 5 years. I was so far away from understanding the challenges and incredible experiences that were ahead of me, and most importantly, the amazing people that would cross my path and help me to become the person that I am today. As I finish this chapter with a sense of mission accomplished, I owe the most sincere “thank you” to those who contributed to this tremendous ride.

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Joana Teixeira

"Hard work is only a prison when you lack motivation."

Malcolm Gladwell

Contents

1 Introduction **1**
1.1 Motivation 1
1.2 The Project 2
1.3 Dissertation structure 3

2 Literature Review **5**
2.1 Procurement 5
2.2 Inventory Management 7
2.2.1 An overview on (*R*,*s*,*S*) systems 8
2.2.2 Multiple suppliers inventory systems 10
2.3 Supplier Selection 11

3 Problem Description **15**
3.1 Production Process 15
3.2 Purchasing Process 17
3.2.1 Forecast 17
3.2.2 Creation of purchasing orders 19
3.3 Preliminary Analysis 20
3.4 Improvement Opportunities 22

4 Methodology **25**
4.1 Proposed Approach 25
4.2 MRP-based Forecast 26
4.3 Replenishment policy 29
4.3.1 Definition of safety stock levels 29
4.3.2 Ordering Decisions 34
4.4 Optimisation Model 34
4.5 The Decision Support System 38

5 Results **43**
5.1 MRP-based forecast results 43
5.2 Scenario evaluation of lead times in safety stock computation 44
5.3 Global Results 46

6 Conclusions and Future Research **49**

A Complementary expressions for the (*R*,*s*,*S*) policy **57**
A.1 Estimation of E(τ) and Var(τ) 57
A.2 Rational approximation to find k 58

B Pseudocode of the MRP Simulation **59**

C DSS Interfaces **61**

Acronyms and Symbols

DSS	Decision Support System
MRP	Material Requirement Planning
KPI	Key Performance Indicator
SKU	Stock Keeping Unit

List of Figures

1.1 Project's timeline . . . 3

2.1 Purchasing Process Model (van Weele, 2009) . . . 6
2.2 Undershoot in a period review system (Silver et al., 2009) . . . 8
2.3 Classification of models according with the planning horizon (Aissaoui et al., 2007) 12

3.1 Production stages in the packaging division . . . 16
3.2 Overview of the purchasing macro-processes . . . 17
3.3 Illustrative procedure to attain coil consumption estimation from the sales rep forecast . . . 18
3.4 Analysis of the product portfolio in 2019 . . . 20
3.5 Forecast accuracy measures for the year of 2019 . . . 21
3.6 Evolution of stock coverage and waste in 2019 . . . 22

4.1 Proposed methodology to improve the purchasing process . . . 25
4.2 Clustering analysis to attain differentiated service levels . . . 31
4.3 DSS Architecture . . . 40
4.4 DSS Homepage . . . 40

5.1 Difference of forecast errors (MAPE) between the devised approach and the AS-IS process . . . 44
5.2 Comparison between carrying costs considering distinct lead times . . . 46
5.3 Analysis on safety stock definition . . . 46
5.4 Comparison of the KPIs between the current and the proposed purchasing process 47

C.1 Importation Form . . . 61
C.2 Suppliers' Parameters . . . 61
C.3 Warnings sheet . . . 62
C.4 Interface to handle urgent coil requirements . . . 62
C.5 Output of replenishment algorithm - coil weekly net requirements . . . 62
C.6 Scheduling of purchasing orders . . . 63
C.7 Validation dashboard . . . 63
C.8 Report . . . 63

List of Tables

4.1 Example of the delivery performance for one specific supplier 33
4.2 Table of notation for the optimisation model. 36

5.1 Comparison of the service level and weeks of stock coverage for the tested scenarios 45
5.2 Service level attained per ABC quadrant 47

Chapter 1

Introduction

1.1 Motivation

Nowadays, a rapidly changing environment is pushing firms to improve their functional processes, which requires a high level of collaboration and coordination among all departments. When it comes to integration of purchasing processes, a close link with both production planning and demand management is crucial for the achievement of strategic and operational goals (Foerstl et al., 2013). Nevertheless, this connection represents itself a great challenge as the increasing complexity of supply chains creates unpredictability in the external supply process, deviations from production plans and uncertainty in demand forecasts (Graves, 2011).

The volatility of today's markets can result in an increased reliance on high stock levels to cover the unavoidable deviations between demand and supply, mainly when firms don't own enough flexibility to cope with both external and internal sources of variability. However, a growing awareness regarding the effects of excessive inventory on company's profitability has been fostering the application of algorithms to improve both accuracy and granularity of inventory management, production scheduling, and demand planning processes (McKinsey&Company, 2018).

In order to thrive in such a competitive era, industrial manufacturers are focusing on improving demand responsiveness as well as generating coping mechanisms to address raw materials price fluctuation (IndustryWeek and Kronos, 2016). The company at stake in this project operates in the metal packaging industry, having cold rolled steel as the main component of its manufacturing process. This raw material has been experiencing significant price increases since 2015 (Statistics, 2020), which creates even more challenges to efficiently reduce costs.

On the other hand, the reinforcement of global sourcing agreements is responsible for the lengthen of order-cycle times in manufacturing industry. As wider time windows entail more uncertainty, companies begin to reveal some weaknesses regarding the proper planning of raw material requirements and its subsequent acquisition (Monczka, 2011).

It is well established in the literature that the purchase of raw materials is perceived as a strategic management decision, as well as a weapon for providing competitive edge for manufacturing intensive firms. Furthermore, according to Fitzgerald (2002), the purchasing process as a whole is now able to affect company's profitability faster and more fiercely than the remaining corporate functions.

In this case study, the purchasing process is empirical and completely dependent on the expertise of key process owners. Moreover, the conversion of sales forecast in raw material requirements does not take into consideration the complex manufacturing context of the company and, despite the importance of supplier selection in the reduction of overall costs, the allocation of orders does not follow any decision-making framework. Thus, it is of the utmost importance to adopt a new holistic and integrated purchasing process capable of systematising quantities and timings of purchases while integrating all business constraints of the company.

1.2 The Project

This dissertation arises from an ongoing consultancy project with a portuguese player in the consumer goods packaging industry. The flexibility to offer customised solutions for several customers positioned in distinct sectors is key to sustain the company leading position in the Iberian market. Hence, the factories located in Portugal, Poland and Spain produce a wide portfolio of tinplate aerosol and general line cans, whose production relies on the processing of cold rolled metal sheets.

The global trend towards leveraging data to increase operational efficiency exposed vulnerabilities regarding the ability to buy the right amount of coil consistently. In fact, the current purchasing process is done empirically and lacks the use of analytical tools to improve decision-making, which jeopardises the achievement of optimal inventory levels across the different raw materials. Additionally, as the company already owns the technology to gather real-time information throughout the manufacturing process, the main stakeholders recognise the long-term benefits of converting that data into actionable knowledge to attain substantial benefits.

In an effort to redefine the purchasing process, the end goal of this project is to provide a Decision Support System (DSS) to support the acquisition of coils required for the production of metal packages. With the aid of a more robust forecast process and an embedded methodology that reproduces a Material Requirement Planning (MRP) system to convert sales previsions into productive needs, the devised tool will be able to place suggestions to the process owner after the integration of all relevant parameters and inputs.

In Figure 1.1, the several activities comprised by the project are outlined with the respective dates and milestones. The initial phase requires a close collaboration with both purchasing and planning departments to ensure a full understanding of the as-is situation. Afterwards, the focus shifts towards providing a more reliable starting point to the DSS. In addition to readjusting the processing of the forecast delivered by the sales rep team, this stage addresses the need to convert sales forecasts into coil necessities. This is accomplished through an end-to-end replication of the manufacturing process, whose fundamental principles are identical to the ones of a MRP system. Ultimately, this methodology allows the application of a suitable time lag between the moment of sale and the beginning of the manufacturing process, enabling the estimation of future coil consumption. Next, the fourth stage is the definition of a suitable replenishment policy. Starting with a well-grounded computation of safety stock levels across the several raw materials, the aim of this step is to provide the final inputs for the optimisation of the purchasing orders.

The final step before the construction of the DSS itself consists in the development of a mixed-integer linear programming model that will support the placement of purchasing orders. The main outputs of the model are the definition of the quantities of raw materials to be acquired, the timing of the purchase and the allocated supplier. Finally, all the previous steps come together in the development of the main deliverable: a Decision Support System that will facilitate the implementation of the intended holistic purchasing process.

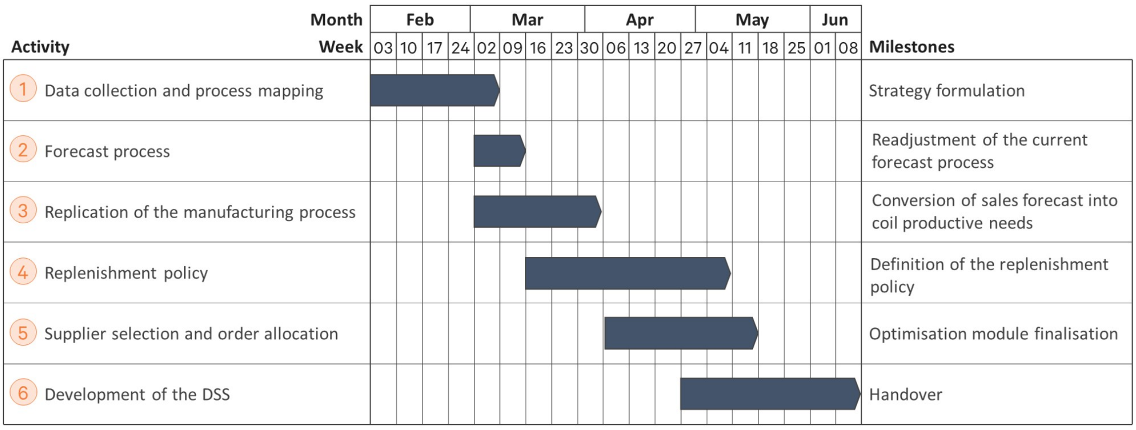


Figure 1.1: Project's timeline

1.3 Dissertation structure

The present dissertation is organised in six chapters with the following outline:

Chapter 2 elaborates on the current literature of the relevant topics for this dissertation. Besides a broad analysis of procurement, this chapter also presents an overview of the state of the art in the fields of inventory management and supplier selection.

Chapter 3 provides a detailed description of the problem being addressed in the company. Additionally, a preliminary analysis of the problem at hands is conducted and the main improvement opportunities are summarised.

Chapter 4 structures the methodology followed to solve the problem, covering the logic that supported its elaboration. After the presentation of a brief summary of this work, it follows an in-depth description of each stage of the methodology. This chapter also discloses the functionality of the DSS itself.

Chapter 5 depicts the preliminary results obtained in the particular case of the studied firm. After providing some results regarding the forecasting process, an analysis that supports some of the heuristics incorporated in the methodology is provided. Lastly, it describes the final outcomes of the project.

Chapter 6 draws the main conclusions of this study, stating some of the shortcomings of the methodology and discussing several future research directions to enhance it.

Chapter 2

Literature Review

This chapter aims to introduce the theoretical background that steered the development of the current project. The first section contains a broad analysis of procurement and its importance in the modern world, giving particular emphasis on the purchasing function. In Section 2.2, the main inventory control systems and its principles are described as an intent to provide context of relevant concepts embedded in the implemented methodology. Also, it is presented an overview of the research efforts in multiple suppliers inventory systems. Finally, Section 2.3 elaborates on supplier selection, addressing its integration with inventory management.

2.1 Procurement

Procurement defines the totality of activities responsible for providing a company with the goods it requires but does not produce itself (Arnold, 1998). Cost reduction pressures and the need for high responsiveness have been pushing companies to focus on their core competencies, fuelling the penetration of outsourcing trends (Monczka, 2011). Darr (2020) states that greater levels of division of labour within supply chains result in higher percentages of purchasing costs in the final product – procurement depth – in relation to the respective production shares. Furthermore, an analysis regarding “Key figures of manufacturing industries” reveals that procurement costs account for 56,3% of the gross production value for the manufacturing industry, underlining the importance of the purchasing process regarding the reduction of operational costs (Destatis, 2019).

The implementation of the best procurement practices provides competitive edge through cost reductions, optimisation of inventory and improvements in customer service (Carter and Yan, 2007; Hassanzadeh et al., 2014). One of the main aspects contributing for such a powerful influence is explained by the profit-leverage effect of supply savings, measured by the increase of profit originated from a decrease in purchasing costs. Despite the challenging nature in reducing overall purchasing costs, Monczka (2011) highlights that it would be necessary a significantly larger increase in sales to generate the same effect in profit.

van Weele (2009) breaks down the purchasing process into a sequence of six steps, from a more strategic perspective to the actual acquisition of goods, as depicted in Figure 2.1 Nonetheless, the link to the internal customer prior to the purchasing function pinpoints the connection with other functions of an organisation. Hence, several studies conclude that cross-functional integration of the purchasing function is key to align its procedures with internal requirements and, ultimately, to address the achievement of competitive goals (Kotabe and Murray, 2004; Foerstl et al., 2013).

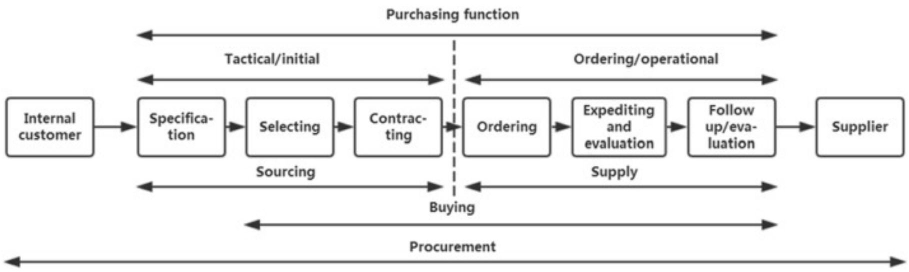


Figure 2.1: Purchasing Process Model (van Weele, 2009)

Previous research points out that even though many complex products need relatively low production time, the acquisition of materials required for the manufacturing operation usually entails long lead times, forcing procurement decisions to be based upon product forecasts (Jayaraman et al., 1994). In Monczka (2011), the lengthening of order-cycle times arises as a consequence of the reinforcement of global sourcing agreements. Therefore, firms deal with extended planning horizons and face higher and higher degrees of uncertainty, which jeopardises their ability to plan material requirements accurately.

Graves (2011) identifies three types of uncertainty that can affect productions plans and, consequently, procurement processes: unpredictability in external supply of materials, deviations in manufacturing lead times and, finally, inaccurate forecasts. Given that Material Requirement Planning (MRP) systems are widely used to define both quantity and timing of internal needs, there are numerous discussions on literature regarding the negative impacts of uncertainties in these systems (Gupta and Brennan, 1995; Enns, 2002).

In their review of MRP-planned manufactures, Koh et al. (2002) state that approaches to cope with uncertainty depend on the kind of uncertainty, the severity of its effect, and also on company preferences. Furthermore, the authors identify two main perspectives to cope with uncertainty: Buffering and Dampening. The work of Zhao et al. (2001) regarding safety stocks methods in multilevel systems and also Plenert (1999) vision to create safety capacity in production fall under the first category, as they consist in purposely maintaining excess of resources in a work center. Within the second category, several authors suggest alternatives to reduce the Master Production Schedule nervousness[1] (Ho and Carter, 1996; Li and Disney, 2017) and also the usage of safety lead times whenever the problem is estimating theoretical lead time values (Whybark and Williams, 1976). Van Kampen et al. (2010) compares the effect of safety stocks and safety lead times, concluding that despite providing more flexibility, lead time approaches result in higher inventory levels.

[1]Constant plan changes

According to Kruger (1997), many firms handle uncertainty by intentionally driving MRP quantities higher than expected demand, which causes excessive levels of inventory mainly on materials common to several products. Additionally, considering that procurement key-owners are constantly under pressure to reduce inventory costs, this author also believes that they might second-guess the MRP system and order different quantities than suggested.

The practical issues concerning procurement management have been fostering the implementation of frameworks targeted to enhance decision-making processes within this field of action. In Moynihan et al. (2006), the need to replace intuitive and non-quantifiable methods employed by human decision makers is discussed, highlighting the benefits of using operational research models and management science towards more supported judgments. While most previous papers only address the use of DSSs to assist supplier selection and optimise ordering time (Ronen and Trietsch, 1988; Ghodsypour and O'Brien, 1998; Lindgreen et al., 2009), the current project also aims to better estimate internal needs and place suggestions of purchasing quantities in order to accomplish proficiency in the raw materials purchasing process.

2.2 Inventory Management

Inventory is defined as the total amount of stock of any item or resource used in an organisation (Jacobs and Chase, 2018). From the main reasons to hold inventory identified in Muller (2011), fluctuations in demand, deviations from previously agreed lead times with suppliers and quantity discounts are the ones with more relevance for companies like the one at stake. However, in order to make assertive decisions in terms of defining inventory levels, organisations must consider inherent costs of owning inventory such as capital, storage, risk (such as obsolescence and damage) and ordering costs (McDonald, 2009).

In Jacobs and Chase (2018), an inventory system is defined as the set of policies that control the amount of stock and determines its optimal levels, as well as when it should be replenished and how large the orders should be. Silver et al. (1998) describes the four most notorious inventory management policies applied in single-stage problems. The (s,Q) and (s,S) systems assume a continuous review, in which a replenishment is made whenever the inventory position drops to the reorder point s or below. In contrast with the fixed order quantity Q characteristic of the first system, the replenishment quantity of the (s,S) system is the one that raises the inventory position to the order-up-to level S.

However, despite the higher carrying costs resulting from adopting a periodic review, a rhythmic and predictable approach is better suited for the company at stake. Hence, the focus will shift towards (R,S) and (R,s,S) systems, that establish a period of time R between two consecutive updates of the inventory position. The fundamental principle behind the (R,S) system is to raise the inventory position to the intended level S every R units of time. On the other hand, (R,s,S) combines both (s,S) and (R,S) systems, thus using the parameter s as the trigger to order enough quantity to reach S. Bijvank and Vis (2012) highlight the fact that several literature has proven (R,s,S) as the optimal policy under the backorder assumption. The authors further justify the popularity of this system by demonstrating that the average cost increase in relation to the optimal policy is disposable even under a lost-sales environment, which represents an alternative assumption to backordering.

The present case study underlines a multi-stage manufacturing situation, which is conceptually identical to a multi-echelon logistic system (Silver et al., 1998). Under these specific networks, Smits (2003) distinguishes between two distinct control concepts: decentralised and centralised. While the first one sticks to the individual inventory position of the considered echelon, the centralised control conducts the ordering decisions based on the state of the system as whole – base stock control system. An important concept used in base stock control system is the echelon inventory, which encompasses its physical stock plus the downstream stock points that have not been committed to outside customers. The decisions rules and equations resulting from Silver et al. (1998) analysis on single-stage problems are considered valid by the authors through this centralised standpoint, adding the fact that replenishment should be based on actual final goods customers demand.

2.2.1 An overview on (*R,s,S*) systems

The work of Silver et al. (2009) acknowledges that the reorder point s is achieved at a random instant between reviews, which generates undershoots of the reorder point prior to the replenishment trigger. The authors present a novel approach that perceives a typical (*R,s,S*) system as a continuous review model with an "effective" lead time $L+\tau$, in which τ is the time elapsed from the moment that the inventory drops to the reorder point until the next review, as shown in Figure 2.2. By using a diffusion model, the reorder point and order-up-to level are determined such that a desired fill rate and average time between replenishments is achieved. This occurs under the assumptions that demand is normally distributed, there is a complete backordering under stockout situations, and the replenishment lead time is constant.

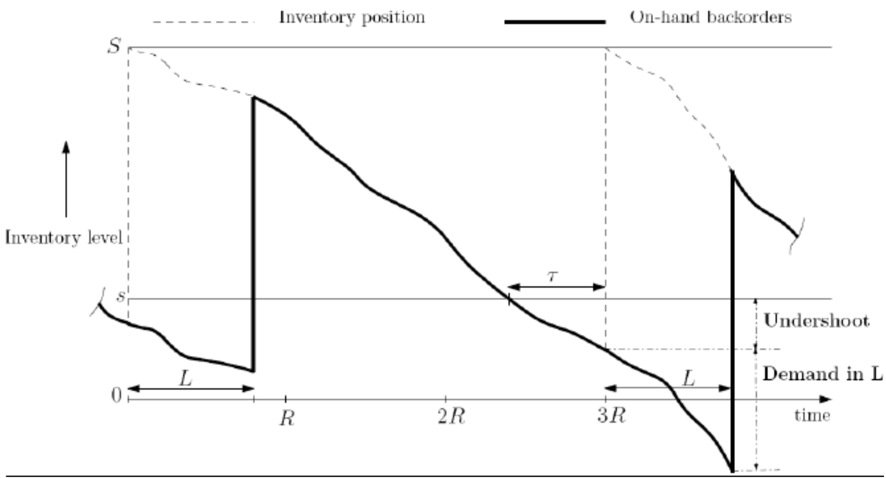


Figure 2.2: Undershoot in a period review system (Silver et al., 2009)

The notation used in the scope of this research is the following:

P_2	Desired value of the fill rate
n	Desired average number of review intervals between consecutive replenishments
L	Replenishment lead time
τ	Random variable representing the time elapsed from when the inventory position hits the reorder point until the next review instant
k	Safety factor
μ	Average demand in a unit time interval, in units
σ	Standard deviation of demand in a unit time interval, in units
CV	Coefficient demand variation in a unit time interval ($\frac{\sigma}{\mu}$)
X	Total demand in $L+\tau$, in units
σ_X	Standard deviation of X, in units

Since it is not possible to develop analytical expressions to determine the moments of τ, these values are determined according to Silver et al. (2009) approach, which can be found comprehensively in appendix A. The procedure they suggested for determining the mean and standard deviation of X is specified in equations 2.1 and 2.2. In Sousa (2013), the author complements the variability of the demand with the uncertainty of the lead time itself. The variability of the lead time is also addressed in Silver et al. (1998), highlighting that increased safety stock is required to protect against the additional uncertainty caused by lead time variability.

$$E(X) = (E(\tau) + L) \cdot \mu \tag{2.1}$$

$$\sigma_X = \sqrt{[E(\tau) + L] \cdot (CV)^2 \cdot \mu^2 + Var(\tau) \cdot \mu^2} \tag{2.2}$$

Following the principles of Silver et al. (2009), the determination of k is computed according with 2.3, where G_u is the unit normal loss function calculated with the intended fill rate and n. The reorder point s is obtained by adding a safety stock to the expected value of demand X as shown in equation 2.4. Finally, the appropriate order-up-to level S is calculated through equation 2.5. This procedure will be adapted in the present work in order to calculate suitable safety stocks that account for the variability of both demand and lead time. However, the process will not be completely replicated due to the existence of a multi-sourcing setting, and consequently variable lead times, which will be further detailed in this chapter.

$$G_u(k) = \frac{(1 - P_2) \cdot n \cdot \mu}{\sigma_X} \tag{2.3}$$

$$s = E(X) + k \cdot \sigma_X \tag{2.4}$$

$$S = s + n \cdot \mu - E(\tau) \cdot \mu \tag{2.5}$$

2.2.2 Multiple suppliers inventory systems

According to Berger et al. (2004), many firms are now using long-term partnerships to acquire more favourable contract terms, and ultimately acquire both high-quality and low cost components. However, Minner (2003) states that many purchasing managers still tend to favour multiple sourcing to mitigate disruption risks and reduce firms dependency on a single supplier. In the updated version of the overview of inventory models with multi-sourcing options, Yao and Minner (2017) pinpoint the challenges of finding optimal policies if sourcing occurs from more than two suppliers with random lead times or if the lead time differences are over one period. The latter involves the possibility of order crossovers, which occur when replenishments do not happen in the same order as they were placed (He et al., 1998). Robinson et al. (2001) points out that whenever a "second order" is received before a "first order", the inventory position at the moment of the arrival of the first order is greater due to the occurrence of the crossover, which ultimately result in fewer shortages but also significant excess of inventory.

The most typical policies studied in the existent literature are the constant order policy (COP), single-index policy (SIP), dual-index policy (DIP) and order splitting policy (OSP) (Yao and Minner, 2017). Chiang (2002) explores the possibility of expedite orders with a premium cost whenever the inventory position falls under a warning point, thus adding an expediting level E to the familiar (s,Q) system. On other hand, Arıkan et al. (2014) develops a simulation model to determine the reorder point and order quantity under the assumption that expedite orders are triggered to fulfil unmet demand.

While single-index policies place both regular and expedited orders considering the stock on hand plus all the goods on order, dual-index policies conduct expedited orders based only in the amount of goods that will arrive in the expedited lead time (Scheller-Wolf et al., 2007). Despite the second approach being considerably more complex, single-index policies provide optimal solutions when the lead times differ by only one time unit (Whittemore and Saunders, 1977), which does not occur in the present case study.

Veeraraghavan and Scheller-Wolf (2008) presents a dual-index-base-stock policy as an easy implementable and robust solution for a dual-sourcing setting. This heuristic policy comprises the tracking of both expedited and regular inventory position, computing the two order-up-to levels using a simulation-based procedure. While the regular inventory encompasses the on-hand inventory and all the orders due to arrive in the next l_r periods, the expedited inventory covers the next l_e periods, where l_r and l_e represent the regular and expedited lead time, respectively. Building on this research, Sun and Van Mieghem (2019) include a third parameter besides the two order-up-to levels, which consists in an upper bound to the slow-order quantity that ultimately provides the policy with a crucial order-smoothing procedure.

Notwithstanding the extensive literature on multiple sourcing, it was not possible to find an approach that takes into account all the specific characteristics of the present case study. Likewise the mentioned research, a vast majority of studies builds on the existence of a regular and an emergency mode of supply. In other words, there is a complete disregard of several specifications of suppliers, and thus the possibility of the most economic supplier for the company differ according to timings and the amount of material that it needs, which significantly undermines the methodology of the revised approaches within this section. In an effort to provide a simple but effective mathheuristic under such complex circumstances, it will be further examined the integration of inventory control policies with supplier selection through mathematical programming models.

2.3 Supplier Selection

The end-goal of supplier selection is to determine which suppliers should be chosen to meet demand needs and how much order quantity should be assigned to each supplier (Guo and Li, 2014). In their review of methods supporting supplier selection, De Boer et al. (2001) propose a framework that covers the different stages of the process: problem definition, formulation of selection criteria, pre-qualification of suitable suppliers and the final selection. According to Mendoza and Ventura (2012), the vast majority of research covers the last stage of the framework, which will be the main interest under the scope of the present project. These methodologies are often split into weighting models and mathematical programming models. In this research, mathematical models are acknowledged as the most appropriate technique due to their ability to optimise an explicitly formulated objective while considering a broad set of constraints that can either be imposed internally or externally.

The first papers addressing vendor selection issues can be traced back to the 1950s, where linear programming and scientific computations were taking their earliest steps (Aissaoui et al., 2007). Since then, several research has been published within this field, being usually targeted to specific problem settings. In Jayaraman et al. (1999), a mixed integer linear programming is formulated to determine the set of suppliers and allocate demand, considering lead time, quality and storage capacity restraints. Additionally, Zhang and Zhang (2011) consider restrictions on both minimum and maximum order sizes. Given that quantity discounts are a common practice among suppliers, Lee et al. (2013) incorporate both all-unit and incremental quantity discounts in their model. In terms of long-term contractual supply commitments, Bonser and Wu (2001) proposed an approach split in two different stages: firstly, the minimum contract purchases for each month are determined in the beginning of the year; then, detailed procurement decisions are settled in a monthly basis resorting to up-to-date information of demand and spot prices.

Under single objective models, additional criteria such as quality and lead time is considered in restraints, which means that they are weighted equally. Thus, some researchers address the inherent multi-criteria nature of the decision by using multi-objective programming and goal programming methods to reallocate criteria from the constraints (Aissaoui et al., 2007). Usually, these approaches enable the assessment of the trade-offs between price, quality and delivery (Chaudhry et al., 1991; Weber and Ellram, 1993). Ghodsypour and O'Brien (1998) propose the integration of analytical support process with linear programming, such that qualitative factors can be insightfully embedded in supplier selection. A more sophisticated version of this methodology, designated by analytical network process, is applied in the work of Sarkis and Talluri (2002).

Mendoza and Ventura (2012) further categorize the existent models whether they include or not the inventory management of the purchased items as part of the decision. Pazhani et al. (2016) identify the determination of the optimal inventory policy and the selection of vendors from which to purchase raw materials as the two main targets of research on supply chain optimisation. The authors believe that solving these two problems individually might yield two sub-optimal solutions instead of an integrated approach.

Nonetheless, De Boer et al. (2001) states that only a few studies allow the scheduling of orders over time, implying that inventory management is disregarded in the vast majority of the existent literature. Figure 2.3 shows the classification presented in Aissaoui et al. (2007) about the horizon of the process of supplier selection. This research emphasises the increased potential of multiple period models to yield better procurement plans, mainly because of the possibility to balance ordering costs with holding costs. From the benefits identified by the authors, the consideration of the trade-off between receiving quantity discounts and bearing higher inventory costs resultant from buying larger lot-sizes is particularly relevant for the present case study. The research based on the economical order quantity (Rosenblatt et al., 1998; Ghodsypour and O'brien, 2001) will not be further developed because it only focus on the division of the economic order quantity among the suppliers, instead of defining variables to determine the quantity purchased in each one of the periods.

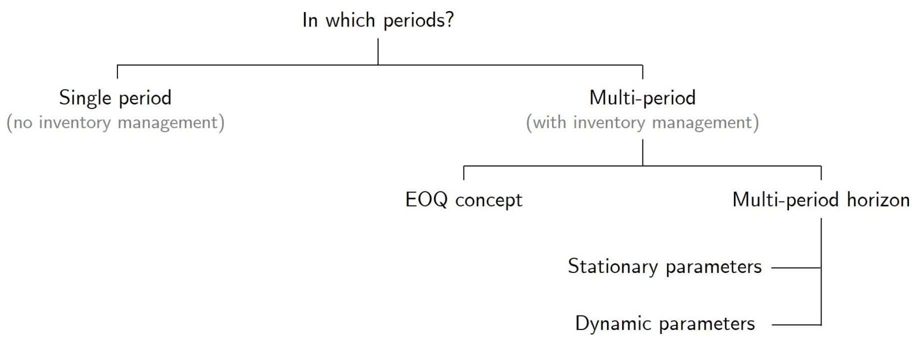


Figure 2.3: Classification of models according with the planning horizon (Aissaoui et al., 2007)

Two distinct models elaborated by Mendoza and Ventura (2012) determine appropriate levels of inventory such that the total annual cost, which includes ordering, holding and purchasing costs, is minimised. By assuming a constant demand rate at the manufacturer's site, the authors establish a predetermined size of the orders allocated to each selected supplier. The second model follows the same premises apart from the fact that the order quantities allocated to all the selected suppliers are of equal size Q. Pazhani et al. (2016) extend the mathematical model to multi-stage models, allocating orders to supplier at stage 1 while simultaneously minimising total costs across the whole system, thus by considering echelon inventory costs instead of conventional holding costs. The assumption of constant demand rate is also in place.

Since stationary inventory policies with constant demand could be too simplistic in real applications, many authors began to seek for new alternatives to handle with stochastic demand. Guo and Li (2014) propose a mixed integer non-linear programming model for a multi-echelon system under a continuous review system (Q,R) and stochastic Poisson demand. The authors assume that is not possible to split orders because that would imply a identical (Q,R) policy independently of which supplier is selected, preventing the establishment of different safety stocks for distinct lead times. In Kang and Lee (2013), a stochastic lot-sizing model with multiple suppliers in which demand follows a normal distribution is constructed. The total costs include the whole costs in the planning horizon and the model considers both the existence of quantity discounts and safety stocks, with the lasts being perceived as the expected ending inventory levels of each period.

According to Tunc et al. (2011), using stationary demand rather than non-stationary can result in meaningful costs, specially under high demand variability conditions. Thus, it is given particular emphasis to the work of Purohit et al. (2016), that comprises the development of an integer linear programming model that simultaneously selects vendors, finds optimum replenishment schedules and determines quantities to fulfil non-stationary stochastic demand in discrete time periods. In contrast to the introduced research, these authors find the accumulated replenishment quantities and on-hand inventory of every period before running the model itself. These quantities are determined according to the intended fill rate and demand distribution over the planning horizon and integrate the constraints of the model. The investigation of the impact of fill rate and the coefficient of demand variation on costs, inventory levels and allocations also inspired some of the analysis of the present work.

Chapter 3

Problem Description

The purchasing process involves two distinct levels of action: the tactical purchasing and the operational purchasing. While the tactical level focuses on the alignment of the purchasing functions with the firm's long-term goals, the operational level is rather concerned with the actual acquisition of goods. The redesign of such a complex process entails far-reaching implications in several departments of the company. Therefore, a holistic comprehension of the as-is methodologies is required before moving forward to the presentation of the proposed approach.

The main goal of the ongoing chapter is to characterise the devised case and assess the magnitude of the challenge at stake. In order to do so, section 3.1 includes a description of the production process, drilling down afterwards in section 3.2 into the current procedures engaged in the purchasing process. Then, section 3.3 portrays a preliminary analysis and a broad assessment of the key performance indicators (KPIs) to be enhanced based on the data originally available. Finally, the chapter culminates with an identification of the shortcomings of the present framework and a synthesis of the improvement opportunities to be tackled.

3.1 Production Process

The scope of this project is limited to the packaging division, the key process of the company in which cold rolled steel coils are transformed into packages of different shapes and sizes that are either delivered to the final customer or, in case of specific aerosol cans, transferred to the filling division. The production process is shown in Figure 3.1 and has the following main stages:

Primary Cut entails the uncoiling and straightening of the steel. After inspection, coils are cut into metal sheets and transferred to the printing division for preparation.

Preparation, in which metal sheets are varnished with a pre-coating. Several varnishes can be applied to the internal and external side of the tinplate, depending on specific client's requirements. The first one aims at creating a protection layer between the metal and the contained product, while the second is both used to guarantee a strong adhesion of the colours applied in the following stage and to provide a clean appearance.

Lithography involves two main operations: printing and finishing. Firstly, metal sheets are fed into the company's printing machines in order to produce designs previously agreed with the final customer. Then, finishing varnishes are applied on top of the colours to prevent the direct contact with the skin and to refine can's overall appearance. Each printing machine has its own set of specifications and each printing order must follow a specific sequence of colours, which demonstrates why this procedure is the overall bottleneck of the manufacturing process.

Secondary Cut comprises the cut of metal sheets into individual bodies or metal strips that will further feed the stamping process.

Stamping represents the last stage of the production of components. These components are stamped accordingly to the format of the can they will fit into.

Assembly merges the can bodies with the respective components through a rounding and welding process. After performing the required leak-tests to ensure a high-quality finished product, the packages are stored in the warehouse until the delivery moment.

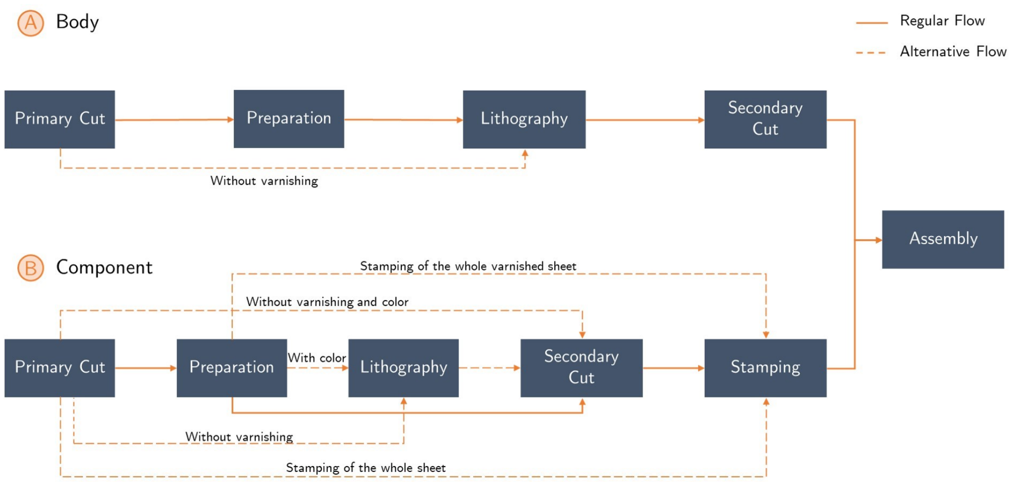


Figure 3.1: Production stages in the packaging division

It is important to understand that as we advance towards the final stage, the product gets more and more attached to specific client's requirements. For this reason, downstream processes usually follow a make-to-order (MTO) strategy to avoid excessive inventory and obsolescence. However, the company currently takes advantage of the existent component commonality, defined in Mirchandani and Mishra (2002) as a manufacturing environment where two or more products use the same components. In other words, standard components are produced under a make-to-stock (MTS) policy to reduce overall lead times. Furthermore, the fact that a multitude of end-products derive from the same type of metal sheets allied with major concerns regarding setup times, result in the diffusion of MTS strategies, mainly during the initial stages of production.

In order to work as intended, the DSS must incorporate all the specific details of the production environment. Besides the quantity restraints, it is mandatory to acquire complementary information on other relevant parameters. For instance, it is not possible to replicate reliably the process without knowing the quantities that trigger a production under a MTS policy and the expected amount of waste in each stage. Moreover, lead times and production cycles (weeks between two consecutive production orders for a specific reference) are vital for applying the necessary time lag between the moment of sale and the beginning of the production process. The implementation of these parameters will be further detailed in chapter 4.

3.2 Purchasing Process

The packaging firm that motivated this case study follows the framework illustrated in Figure 3.2 to manage its purchasing process. Its end-goal is a timely acquisition of suitable amounts of distinct coils required by the production process. In an effort to remain as competitive as possible, the firm promises customers a delivery time that is at least half the order-cycle time[1], which makes the placement of purchasing orders heavily dependent on the information from the sales forecast.

Despite being responsible for some of the challenges in terms of inventory management and supplier selection, it is possible to assume sourcing as exogenous to the scope of the current project. The most relevant macro-processes to analyse linked to the purchasing process comprise the gathering and disaggregation of the forecast provided by the sales reps team and, finally, the creation and allocation of orders conducted by the purchasing manager. An in-depth breakdown of these processes is described on the following subsections.

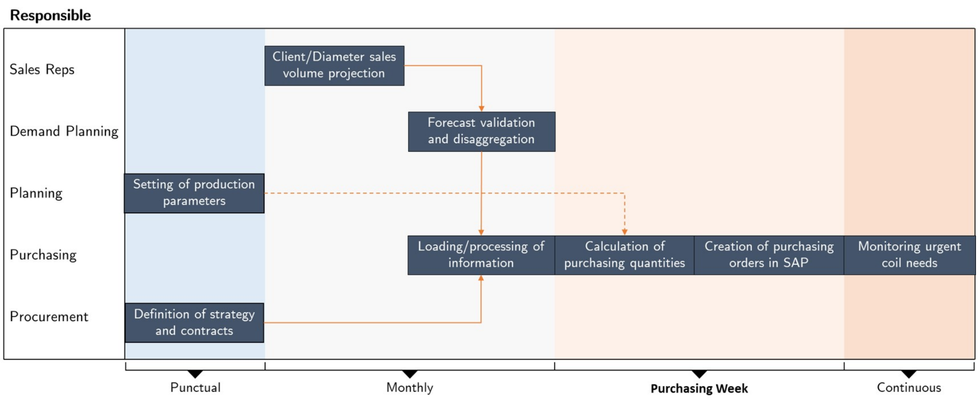


Figure 3.2: Overview of the purchasing macro-processes

3.2.1 Forecast

The sales team maintains a close relationship with firm's clients in order to gain visibility on future demand. According to Carter et al. (2000), the increasing focus on the relationship management with customers to achieve competitive advantage fosters the interdependence among buyers

[1]Currently, the minimum order-cycle time is 8 weeks

and suppliers, resulting in a coordination of internal activities and processes. In fact, there has been a significant effort to increase the collaboration with the customers towards the achievement of a more robust and unbiased forecast.

Nonetheless, not every client has enough maturity to anticipate their own sales, which prevents them to share timely data regarding future purchases. Moreover, in spite of the known benefits obtained with strategic alliances, some don't have sufficient trust to reveal their purchasing intentions in advance. The implications of such occurrences are severe in companies placed further up the supply chain, as is the case, because the forecast accuracy relies heavily in both customer's ability to forecast and their willingness to cooperate.

Even though a significant number of clients is willing to share estimations on their future sales, the sales rep team has no other option but to rely on historic sales to generate a forecast for the remaining cases. Figure 3.3 illustrates the process from which it is elaborated a prediction of coil consumption from the sales rep team initial forecast. By observing its first link (part A), it is possible to understand that the initial forecast is conducted at a more aggregate level - client/diameter - due to clients' lack of certainty to provide an assertive prediction at the SKU level. In other words, the sales team loads projections of the number of cans with a specific diameter that a certain client intends to buy.

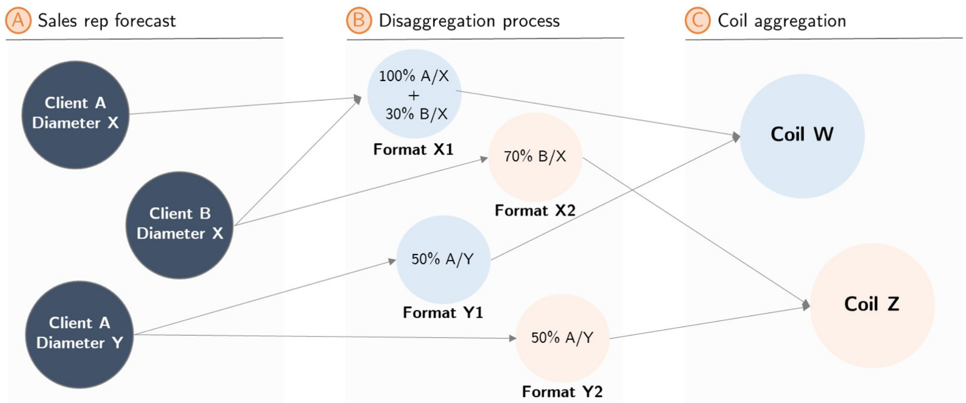


Figure 3.3: Illustrative procedure to attain coil consumption estimation from the sales rep forecast

Afterwards, the demand planning team has the responsibility to validate and disaggregate the forecast, as presented in part B of the Figure 3.3. Firstly, it is performed a calculation of the proportion of sales occurred in the previous year associated with every format contained in each client/diameter. Besides the client, shape and diameter, the format also includes information regarding both height and thickness of the can. In general, previous sales from a specific SKU will be accounted into three different formats: one for the body, other for the lid and, finally, one for the bottom of the can. For simplification purposes, Figure 3.3 only considers can bodies and does not represents the specific formats emerging from the existence of components.

Ultimately, as each format consumes a specific coil, the forecasts of each coil are aggregated, resulting in an overall estimation of required amounts of coil in a monthly basis (part C). The conversion between cans and kilograms of coil is enabled by the bill-of-materials (BOM), in which is displayed the full product structure. Using client A/diameter Y as an example, it is possible to observe that its two formats sold equally in the previous year. Hence, the disaggregation part consisted in dividing the initial prevision by two, allowing a granular prediction of each format. Finally, the last step consisted in adding the inherent amounts of coil estimated for formats Y1 and Y2 to the forecasts of coils W and Z, respectively.

It is important to mention that the company also sells individual components separately. The sales team gathers information on future demand for these components, and the following procedures are the same as mentioned before, which pinpoints the existence of formats without height.

3.2.2 Creation of purchasing orders

The creation and allocation of purchasing orders follows a completely empirical approach, which makes this process completely dependent on the expertise of its key-owner. The main sources of information that support the purchasing manager decisions are:

- Coil and plain metal sheets (F1) stock-on-hand;
- Stock in transit due to previous purchasing orders;
- Historical coil consumption;
- Expected coil consumption for the following months.

Until this moment, there is not a clearly defined reorder point and order-up-to level. Instead, the fundamental logic behind the process is to guarantee that at the end of each month there is enough coverage to endure at least the expected consumption of the next one and a half months. The expected coil consumption is the output of the forecast process covered in subsection 3.2.1, except for extremely steady coil in which historical data is a better proxy to predict the future.

Another important detail comprises the possibility of using alternative coils to address potential shortages. Since raw materials have a high impact on company costs, sheets with different measures are produced from coils with suitable sizes. However, as forecasts are updated every month and customers are continuously placing orders, it is possible to identify unexpected internal requirements without enough time to obtain materials from the suppliers. In these situations, it is possible to allocate unconventional coils with slack of stock to handle the unforeseen demand. However, this adjustment results in higher levels of waste due to the misalignment between the coil dimensions and the intended metal sheets sizes.

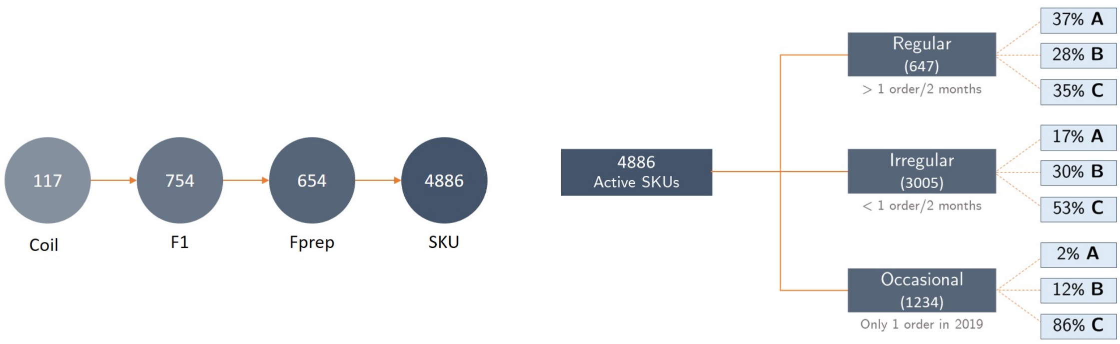
After the identification of the net coil requirements for each month, the purchasing manager allocates each order to one of the possible suppliers. In this stage of the process, the distinct lead times assured by each supplier have to be considered to determine the timing of the purchasing order. Moreover, there are several constraints that restrict directly the quantity of coil to be purchased, such as the existence of minimum order quantities (MOQs) and lot sizes.

The present mindset focuses on the reduction of purchasing prices, thus taking into account quantity discount prices practiced by some suppliers. Additionally, there is a close monitoring regarding the fulfilment of the annual contracts settled in advance with some suppliers by the procurement department. On the other hand, the current approach disregards carrying costs and lacks the support of mathematical optimisation tools to guarantee the consolidation of the best feasible solutions.

3.3 Preliminary Analysis

The present section intends to elaborate on the originally available data, not only to provide a clear overview of the challenging nature of the problem but also to assess the two original KPIs to be enhanced: stock coverage and wastage. It is important to mention that both annual acquisition and carrying costs were added to the vital KPIs, as the devised approach shifted towards the optimisation of purchasing orders based on these metrics.

Although the company provides tinplate packaging to a global market, the portuguese site is the only one that covers the entire production process. Thus, the factory under analysis encompasses the whole range of coils used to produce the 4886 SKUs of 2019. As it is possible to observe in Figures 3.4a and 3.4b, the need to embrace customisation and gather new customers caused a significant ramification within the production process, as well as the existence of products with rather distinct kinds of demand.



(a) Ramification of the production stages

(b) Product segmentation

Figure 3.4: Analysis of the product portfolio in 2019

In Figure 3.4a, the lower number of varnished sheets (Fprep) references in comparison with plain sheets (F1) is due to the fact that most components and certain cans don't need to be varnished before the lithography stage. On the other hand, Figure 3.4b shows the segmentation process conducted on each final good based on sales data from 2019. The products were divided in three categories: regular, irregular and occasional products. Furthermore, the products contained in each segment were evaluated in light of their impact in the total amount sold in that segment through an ABC analysis. An overall strong Pareto effect was identified as 16% of the products account for 80% of the total sales. Despite many A products being sold consistently through the year, there are several relevant products whose demand is intermittent or affected by seasonality. In fact, the existence of seasonality is already recognised by the company and justified by the customers own sales patterns, which in turn are affected by the type of products they sell.

The typical low demand regularity entails serious challenges regarding the forecasting process, thus justifying the need to aggregate predictions in a lower granularity level, as previously explained in subsection 3.2.1. As the forecast of coil consumption is one of the major inputs for the purchasing process, it makes sense to assess its accuracy by comparing predicted values with the reality. Two of the most common metrics used to calculate the accuracy are the Mean Absolute Percentage Error (MAPE) and Mean Percentage Error (MPE or Bias) (Schuller, 2018).

The results of the forecast accuracy obtained in 2019 are shown in Figure 3.5. While the client/diameter measures were obtained through the comparison of predicted sales with actual sales in that specific granularity, the accuracy of coil forecast was assessed by comparing the monthly estimations of coil consumption resultant from the disaggregation of the sales rep forecast with the corresponding actual values of consumption. It appears that higher predictions than reality in terms of client/diameter demand do not necessarily lead to the same path in terms of coil consumption. By analysing the Bias evolution through the year regarding client/diameter forecasts, it seems that the sales rep team seeks to balance previous errors, as overestimation periods are commonly followed by underestimation periods. Finally, the company's MAPE is about 50%, while the overall Bias values are 5% and 7% for client/diameter and coil, respectively.

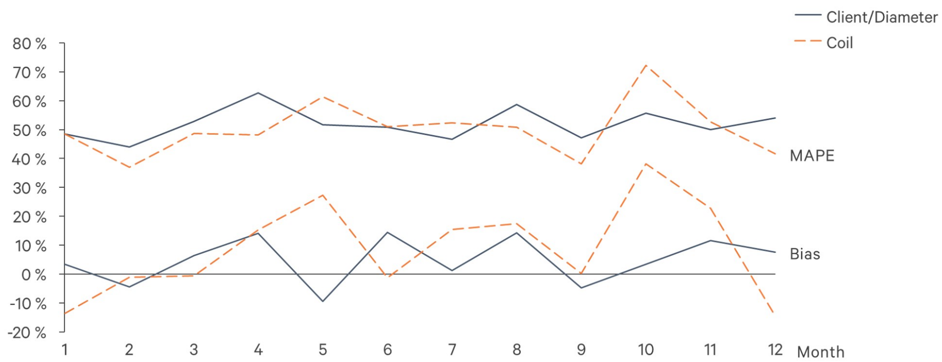


Figure 3.5: Forecast accuracy measures for the year of 2019

As previously mentioned, the main goal of this project is to enhance the purchasing process such that the company is able to reduce its levels of wastage and optimise its stock coverage. The quantity of waste is a proxy for coil availability. In other words, higher levels of waste represent a clear sign that the company is facing shortages of coil. On the other hand, stock coverage represents the amount of time that the firm can operate with the current inventory (see Equation 3.1). This indicator provides guidance on the existence of excessive levels of inventory, which represents one of the main concerns of the company managers.

$$Stock\ Coverage = \frac{Average\ Stock}{Average\ Consumption} \tag{3.1}$$

Even though the previous analysis demonstrates that, globally, the firm overestimated coil consumption only by just 7% in 2019, a close inspection of the carried inventory revealed that unbiased forecasts are not enough to determine optimal purchasing order quantities. In this regard, Figure 3.6 shows the monthly evolution of the aforementioned KPIs in 2019. It is possible to conclude that while metal sheets' stock coverage does not vary much through the year, the stock coverage of coil is gradually increasing, reflecting a buildup of excessive inventory. In the first months of the year, the overall stock coverage was too low, which resulted in high percentages of waste. However, it seems that there's no additional protection from a certain level of coverage. In fact, in spite of the additional inventory, the percentage of waste is actually increasing in the last months.

Bottom line, the firm ended up buying excessive amounts of coil and facing significant shortages simultaneously in the previous year. A preliminary analysis seems to indicate that wastage is minimised when the coverage of coil is approximately the same as the minimum order-cycle times required to acquire this raw material (8 weeks).

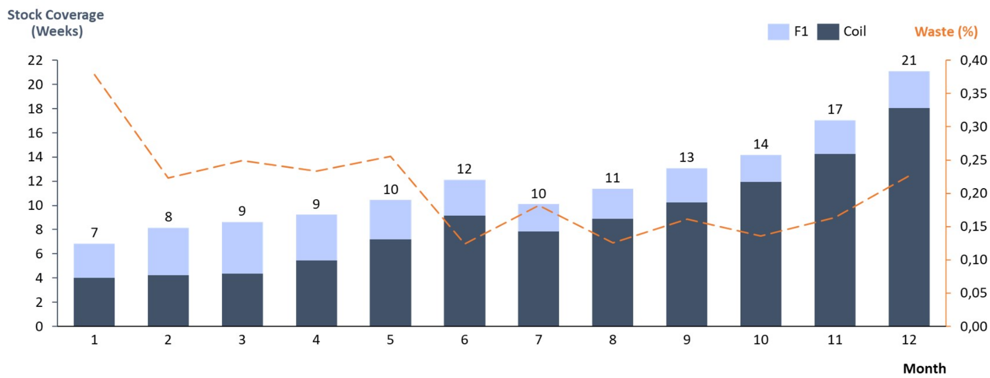


Figure 3.6: Evolution of stock coverage and waste in 2019

3.4 Improvement Opportunities

Until this moment, the firm relied on the many years of experience to apply an empirical approach to conduct the acquisition of its most important and expensive raw material. However, decisions based purely on the expertise of process owners might not be sufficient to strive in today's highly competitive environment. Building on this premise, this section contains the main improvement opportunities in two different areas: forecast of coil consumption and the purchasing process itself.

Forecast of coil consumption

The breakdown of the forecast conducted by the demand planning team uses historical sales from the previous year to define the proportions of disaggregation. Given that the firm must answer to seasonality effects and operates under a fast-changing environment, this approach significantly bundles its capacity to adapt. Moreover, the forecast of coil consumption does not consider any planning or production restrictions, despite their meaningful impact on day-to-day operations. Overlooking parameters such as minimum lot sizes and reorder points can be dangerous given the rather complex operational reality of the company.

On the other hand, the firm only takes into consideration the existence of a productive lead time for its four most important clients. For these customers, the monthly forecast is added and distributed unevenly across the original months, favoring the initial months to guarantee that the coil consumption is accounted prior to the beginning of the manufacturing process. However, apart from these situations, the expected amount of cans to be sold in a certain month is directly converted in expected coil consumption for the same month, when in reality, a significant portion of this consumption will occur in the previous month.

Finally, the lack of systematic indicators to measure the forecast accuracy jeopardise both monitoring and evaluation procedures. Thus, the deployment of dashboards to keep track of the company's current situation should also comprise measures to assess the performance of such an important process.

Purchasing

The definition of order quantities and their consequent allocation to the suppliers is a completely manual process. The absence of a clear inventory policy means that there are not established reorder points that trigger the execution of purchasing orders. Also, nor does the company set safety stocks for the desired service level. In terms of protection against the unavoidable variability of both demand and suppliers lead time (as explained in section 2.2), the process fails to consider the specificity of each coil by systematically guaranteeing a stock coverage of at least one and a half month for each coil, which is being obtained by dividing its expected stock at the end of each month by its expected consumption of the following month. Thus, the definition of safety stocks is driven by the amount of consumption of each raw material rather than the degree of variability, as comprehensively advocated in the literature.

Currently, the purchasing manager considers both coil and metal sheet stocks as a cushion to respond to predicted internal requirements. This approach raises two distinct problems that might have a significant impact on the established KPIs:

- The consideration of metal sheet stock is not conducted insightfully. As distinct metal sheets lead to different final goods, the company might be mistakenly relying on stock that does not fulfill its real necessities at that moment. However, this problem is mitigated by the fact that each kind of metal sheet usually originates a significant number of final goods, which ends up reducing the risks of integrating its inventory position during the purchasing process;

- The stock originated from downstream processes (stock of varnished sheets, lithographed bodies and can ends, components and final products) is not being considered in any situation. Despite being really challenging to predict accurately the productive needs for these stages, the company is not leveraging the existence of extremely high amounts of stock that can provide a safe defense against the uncertainty. Moreover, the acknowledgement of stock for sufficiently stable and reliable materials can ultimately result in reducing overall costs in coils with excessive inventory levels, without compromising the customer service.

Without the support of an analytical tool, the allocation of orders to the several available suppliers is also performed empirically. Nowadays, the purchasing manager relies on certain simplifications to ease the selection of suppliers for each order, which can prevent the achievement of an overall optimal solution. Moreover, as carrying costs are neglected, purchasing orders are often placed too far in advance. Notwithstanding these remarks, the incorporation of analytical tools is not meant to replace the human decision-maker but rather to provide key additional insights. For instance, the fulfillment of contract agreements will continue to require the attention of the purchasing team.

Lastly, the project also aims to implement the creation of automatic operational reports and dashboards that foster a continuous monitoring culture. One of the most important points in this field comprises the deployment of warnings to ease the supervision of urgent coil necessities and guarantee that these situations are handled immediately.

Chapter 4

Methodology

The present chapter addresses the methodology undertaken to overcome the challenges previously identified and to enhance the acquisition of cold rolled steel metal. Firstly, section 4.1 presents the summary of the proposed approach. Then, an in-depth description of each stage of the methodology is provided in sections 4.2 to 4.4, encompassing the MRP-based forecast, the replenishment policy and, at last, the mathematical optimisation model that will ultimately provide suggestions of purchasing orders to the company. The final section briefly introduces the decision support system built on the methodology presented over the outline of this chapter.

4.1 Proposed Approach

The present project followed a three-fold methodology as shown in figure 4.1. The main deliverable of the system comprises the decision support system, which is perceived as an interface to the implementation of the proposed approach. Besides reporting the evolution of the primary KPIs and additional relevant figures, the system will provide recommendations on future purchases and, after the validation of the purchasing manager, places the orders to the suppliers.

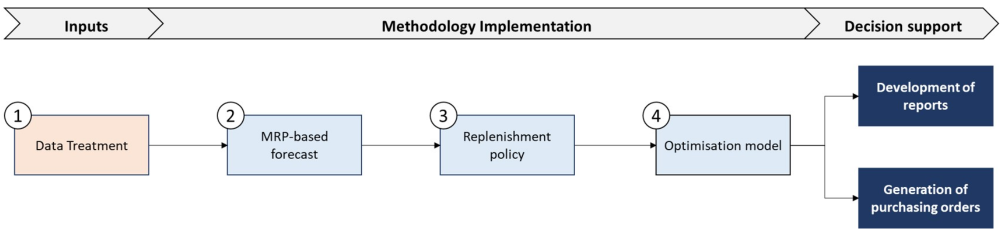


Figure 4.1: Proposed methodology to improve the purchasing process

The first stage encompasses the data retrieval and its following treatment in order to be used in the project's methodology. A strong communication and frequent visits to the facilities were key to achieve a more in-depth knowledge of the main processes and determine the full requirements in terms of information. It is possible to divide the gathered data into three different categories:

firstly, transactional data such as historical sales and inventory records; then, production parameters adjacent to the purchasing process to enable a reliable simulation of the factory; finally, information that was not being properly systematised, mainly related with suppliers conditions.

The second major step results in the adaptation of the forecasting process conducted by the company. The sales rep forecast is incorporated in this stage, although its treatment and purpose is different than what the company had until today. The disaggregation weights were adjusted and the end goal is now to provide a forecast at the SKU level rather than converting right away the client/diameter forecast into coil consumption according to the procedure introduced in section 3.2.1. Then, a simulation model representative of the company's manufacturing process was constructed, capable of reading data inputs and integrate the relevant business constraints and parameters. The inherent principles are the same as a classic MRP system, with the addition of a procedure to handle with the uncertainty of the provided forecast. Ultimately, this step allows the projection of the evolution of stocks through the manufacturing chain, enabling the forecast of coil consumption for a weekly time frame.

The third stage focused on the determination of net coil requirements, which implied the definition of safety stocks that account for the specificity of each one of the existent coils. This implies the assessment of the variability of the process, both on the measurement of the forecast errors and the reliability of the suppliers delivery itself. Furthermore, distinct considerations were tested in order to achieve the best suited parameters for the replenishment.

The steps undertaken so far provide the required inputs to the optimisation model, that further incorporates the cost-benefits trade-offs for a chosen time-horizon and the several constraints of the suppliers. The ultimate goal is to define an optimal schedule of the purchasing orders of each coil in order to minimise the total costs of the system. The outcomes of this process are then validated by the purchasing manager, which enables the attainment of a holistic solution that does not despise the expertise added by the key owner. This duality is fundamental for the fulfilment of contract agreements with suppliers and the usage of alternative coils.

The final step comprises the development of a DSS to transmit the acquired knowledge to a business application with the purpose to aid the purchasing process. Besides enhancing the generation of orders, the tool also allows the assessment of its impact in the defined KPIs.

4.2 MRP-based Forecast

The main motivation behind the simulation of the shop floor comprises the possibility to account high levels of stock in downstream manufacturing processes, as well as incorporating production requirements. As in any MRP system, the scheduling of parts and components required to produce a final good is based on independent demand, that is, the demand of the end product.

The client/diameter forecast provided in a monthly basis by the sales rep team continues to be the starting point to attain a reliable forecast of future coil consumption. However, as the MRP simulation occurs backwards, from the higher-level final goods towards raw materials, a forecast at the SKU level is now required. In addition to this shift of purpose, an in-depth analysis and conversations with the main stakeholders resulted in the readjustment of the disaggregation weights: instead of calculating the proportion of sales occurred in the previous year, these values are now obtained by considering the sales of the homologous period, multiplied by a growth factor, between the current and the past year. This way, we accomplish a compromise between the incorporation of seasonality effects and also the ability to adapt to constant changes in customer preferences.

A Material Requirements Planning system closely interacts with three main sources of information: the bill-of-materials, in which is presented the sequence of production and the quantities of each item required to create each final good; the updated inventory records; and the master production schedule, which specifies how many and when the firm plans to assemble each item. In an attempt to replicate the former information source, the devised system incorporates several parameters that allow to simulate reliably the functioning of the factory when provided with a forecast of the independent demand. These parameters were gathered with the aid of the planning department, resulting in the following list:

(i) *Production quantities rules*

- Minimum lot sizes: minimum quantities to mitigate setup times, respecting both the integral coil cut and the fact that certain items are produced in batches;
- Printing rules: minimum quantities applied only in lithography for general line cans, whose values are calculated based on historical consumption;

(ii) *Planning parameters*

- Production strategy (MTS/MTO): defines whether the production is made in advance or after a customer request;
- Order points: desirable amount of stock for each item, incorporated as a threshold to release production orders;
- Production cycles: minimum weeks between two consecutive production orders;
- Standard lead times: time required to fulfill a production order.

(iii) *Other parameters*

- Scrap rate: percentage of the expected waste.

As most of the manufacturing firms, the company at stake already owns a software system with MRP functionalities. However, the stakeholders acknowledge that the excessive amount of uncertainty at the SKU level disables a blind incorporation of a MRP system to predict coil requirements. For instance, if the company predicts significant sales for a final good with huge amounts of stock, the system assumes that the demand will be fulfilled without the need to produce new cans, and consequently, without consuming coil. However, if the actual customer order is targeted to a distinct final good that does not have the same stock level, the underestimation of coil consumption can ultimately result in stock shortages and production postponement.

In an effort to account stocks through the manufacturing chain and simultaneously cope with the unpredictability, it was created a new measure to be incorporated in the simulation - the uncertainty associated with each item (e.g. metal sheets, components and final goods). This measure is based on historical forecast errors from the last two years, in which the actual monthly amount of sales for each item is compared with the respective forecast.

As previously mentioned, company's products face very distinct patterns of demand, ranging between very constant sales to only receiving punctual orders. Syntetos et al. (2005) categorise demand patterns based on the squared coefficient of variation (CV^2) and also on the inter-demand interval, in which 1,32 is the cutoff value for considering the demand intermittent. The authors argue that under such circumstances, it might not be reasonable to model the demand using the standard theoretical distributions. After testing different thresholds, it was decided that the value of the uncertainty is provided by the difference between the 90$^{\text{th}}$ percentile of the forecast error and the average forecast for intermittent items. On the other hand, the forecast errors for the remaining items are modeled with the theoretical distribution that provide the best fit. At last, the uncertainty value for those items is given by the number of standard deviations that allow to cover approximately 95% of the established distribution (e.g around 95,45% of the values lie within two standard deviations of the mean under a normal distribution).

The more final goods originated from a certain item, the less chance exists of having unrealistic forecasts, as overestimation in some final goods are offset by underestimation among the others. The uncertainty measure captures this effect, resulting in higher values for downstream items, such as can bodies, and lower values for upstream items, such as metal sheets. Uncertainty also reacts systematically to the demand pattern of final goods, accounting higher amounts of stock in predictable items ordered consistently. Having this safeguard against leveraging stock incorrectly and underestimating productive needs, it is possible to move forward to the replication itself, keeping in mind that the goal is to seize the status quo to provide an enhanced forecast of coil consumption.

The pseudocode that comprises a simplified basis for the sequential calculation of productive requirements through the manufacturing chain is presented in Appendix B. The incorporation of the uncertainty occurs right at the beginning, as this measure is deducted from the initial stock level, as long as the amount of stock does not go below the established order point.

Afterwards, the logic of the remaining process is essentially the same for MTS and MTO items, except for the value of the order point itself. As production orders for MTO items only intend to fulfill demand, their order point is set to 0 and the amount of each order will be the maximum between the demand and the value imposed by production quantities rules. On the other hand, production orders for MTS items not only fulfill demand and respect quantity constraints but also restore the stock level above the intended order point. While this threshold is a fixed quantity for downstream items, it is calculated through a desired coverage in weeks for metal and varnished sheets, whose expected consumption is based on historical data from both the homologous and precedent period. Also, it is guaranteed that production cycles higher than 1 week are respected, which occurs mainly for MTS sheets.

The algorithm checks demand from downstream links for each week, removing its amount to the initial stock position. Whenever the stock position goes below the order point, an order is triggered and pulls requirements from upstream levels, adding the amount of expected waste provided by the scrap rate and applying the time lag stated in the standard manufacturing lead time. The process is replicated for each production stage until the primary cut, in which the expected production orders represent the milestone of this stage - the weekly forecast of coil consumption.

4.3 Replenishment policy

The formulation of a replenishment algorithm will ultimately define the weekly net requirements of each raw material. The end goal is to adapt state of the art replenishment policies to the business reality of the company, thus allowing a subsequent allocation of purchasing orders to the most suitable supplier. Since the production plan is made weekly, the proposed replenishment policy is based on a periodic system (*R,s,S*) with a matching weekly review period. Firstly, a comprehensive analysis of the procedures to compute safety stock levels is presented. Then, the following subsection addresses the foundations of the ordering decisions.

The global mechanism of the methodology is grounded on the work presented by Silver et al. (2009), which has been already introduced in chapter 2 as an approach to fulfill a predetermined service level and an intended average time between orders. The choice of this approach can be justified by its huge reputation amongst the literature and also the suitability of the target criteria within the context of the project, as will be further explained in the outline of this section.

To cope with specific requirements of this project, the lead time variability is incorporated and the computation of both reorder point and order-up-to level is performed accordingly to a developed heuristic. The main motivation behind these alterations is the shift in the purpose of the replenishment policy itself: while classical approaches focus on the determination of final order decisions, we are rather concerned in determining the amount of coil that should be arriving to the company each week to fulfill the manufacturing requirements. The transformation of these requirements into actual orders is conducted afterwards, through the use of an optimisation model explained in section 4.4.

4.3.1 Definition of safety stock levels

Prior to the implementation of this project, the company used to define its safety stock levels through a "one size fits all" type of strategy, driven by the average consumption rather than the inherent variability of each coil. As this approach is strongly discouraged within the literature, the implementation of a new safety stock policy that integrates specific characteristics of raw materials is perceived as one of the key elements of the project.

According to Silver et al. (1998), choosing the appropriate approach/measure of service to compute safety stocks depends on the competitive environment of the company. Whenever delivery performance is a main competitive advantage, as is the case of the company at stake, managers usually set demanding service targets instead of explicitly costing a shortage and minimising the total amount of cost. Hence, the safety stock will be based on customer service, whose measure will be the fraction of customer demand met without backorders or lost sales.

Similarly to the work of Sousa (2013), safety stock levels will be calculated following the principles of Silver et al. (2009), but incorporating the variability of lead time, one of the biggest component of uncertainty for the company at stake. The fact that the reorder point s is reached with a time lag τ until the next review moment is the main principle of the model, that further assumes that demand and lead time are stochastic.

In addition to the notation already introduced in chapter 2, $\hat{\sigma}_D$ and $\hat{\sigma}_{\mathrm{L}}$ represent estimators of the standard deviation of forecast errors and the standard deviation of the replenishment lead time, respectively. The standard deviation of demand during the effective lead time is then calculated as in equation 4.1.

$$\sigma_X = \sqrt{[E(\tau) + L] \cdot \hat{\sigma}_D^2 + [Var(\tau) + \hat{\sigma}_{\mathrm{L}}{}^2] \cdot \hat{\mu}^2} \tag{4.1}$$

Recalling equation 2.3, it is possible to conclude that the safety factor k is dependent on several factors such as the desired service level, time between orders and the variability of demand over the effective lead time $L+\tau$. While the rational approximation used to calculate the safety factor k and the analytical expressions to determine the moments of τ can be found in detail in Appendix A, the remaining parameters will be addressed within this section. At last, the safety stock SS is calculated as in equation 4.2.

$$G_u(k) = \frac{(1-P_2) \cdot n \cdot \hat{\mu}}{\sigma_X}$$

$$SS = \sigma_X \cdot k \tag{4.2}$$

Time between orders

Nowadays, the suppliers of the company are not prescribing time intervals to accept purchasing orders. Moreover, they do not charge inbound logistic costs, which enables the company to place orders unrestrictedly over time, as long as minimum order quantities and lot sizes are respected. Hence, given the absence of additional ordering costs, the implementation of a just in time framework (that is, ordering only when it is necessary) would result in a weekly placement of orders for raw materials with an average weekly consumption above the imposed minimum.

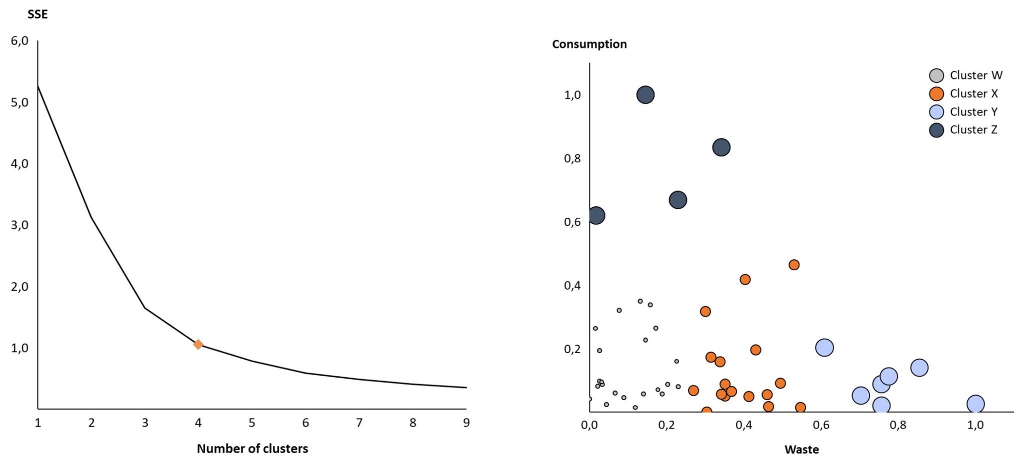
However, stakeholders were concerned that changing dramatically the pace of the orders could damage the good relationships between the company and the suppliers. For that reason, the intended interval between orders n was set for two weeks.

Service Level

The definition of service levels is often associated with a previous ABC inventory classification, in which demand value and demand volume are the most common ranking criteria (Teunter et al., 2010). The decision to use demand value as a proxy for service levels can be justified by the fact that coils represent the beginning of a complex manufacturing process, without which several downstream processes would be compromised. In fact, coils with higher demand are either the source of many final products manufactured by the company or source of key products that have high weights in the overall sales of the company. Either way, the proposed methodology intends to guarantee a really low number of shortages for these raw materials, prioritising their service level in relation to lower demand ones, whose absence does not cause such severe impacts to the company.

Notwithstanding the usefulness of an ABC classification, it was exploited the opportunity to incorporate the frequent substitution processes among coils that occur in the company. It is important to recall that the substitution is only possible under the existence of coils with the same specifications but larger dimensions than the one in shortage. Hence, the main goal is also to provide excellent service levels to raw materials whose substitution entail high levels of waste, or, in most extreme situations, is not possible at all.

The coils were then divided into different clusters through the k-means method introduced by MacQueen et al. (1967). The chosen explanatory variables are the average demand volume and the minimum percentage of waste under substitution, whose values were previously normalised.



(a) K-means Elbow method (b) Clustering results

Figure 4.2: Clustering analysis to attain differentiated service levels

The clustering analysis is displayed in Figure 4.2. Despite its simplicity, the elbow method shown in Figure 4.2a is an effective visual approach to select the number of clusters, whose principle consists in selecting the number of clusters from which the distortion slowly decreases (Kodinariya and Makwana, 2013). The distortion comprises the within-cluster sum of the squared errors (SSE) and is the measure that the k-means algorithm aims to minimise. Having selected 4 as the ideal number of clusters, Figure 4.2b presents the final segmentation obtained with the clustering analysis. While the color of the circles segments the coils according to the respective clusters, the size of the circle indicates the intended service level. Thus, it is possible to observe that clusters Y and Z have the same and the highest service level, followed by clusters X and W.

The clusters Y and Z correspond to the materials that should be handled more carefully, that is, that have high demand volume or considerable percentages of waste generated under substitution processes. The fact that coils with far higher consumption have a significant number of alternatives explains the lack of coils with high demand and considerable waste simultaneously. It was then decided to set a service level of 99% to the products that belong to these clusters. Furthermore, coils with no chance of substitution (that were not incorporated in the cluster analysis) have the same target, in order to avoid situations where the company have no other option but to postpone the production. Building on the same logic, the remaining clusters X and W were assigned with service levels of 97,5% and 95%, respectively. These values were obtained after several tests and posterior validation with the company.

Lead time

Unlike the studies that inspired this methodology, the definition of the lead time represents itself one of the most challenging procedures within the computation of safety stocks. Instead of having only one supplier available, the company has at its disposal a range of distinct suppliers depending on the raw material. As the selection only occurs after the implementation of the replenishment policy, there is a probability that the lead time set for the calculation of the safety stocks is not the one that will actually take place.

Nearly 25% of the coils can be ordered to European (minimum lead time of 8 weeks) and Asian suppliers (maximum lead time of 16 weeks). Under these conditions, the selection of a lead time value for the calculation of safety stock can occur with a potential disparity of 8 weeks. In order to tackle this drawback and ultimately choose the most suitable heuristic for the company, a simulation of the previous year of 2019 was conducted with three distinct premises: applying the minimum lead time, the average or the maximum one. The end goal is to assess the impact of these variations in terms of the service level and carrying costs. Given the importance of this analysis to the project, its results can be found in detail in chapter 5.

The calculation of the standard deviation of the lead time is also a required variable to incorporate the uncertainty in the external supply of materials. Thus, it was gathered historical data that contained the expected and actual date of shipment[1] for each one of the coils. In order to accommodate the existence of multiple suppliers, the differences between real lead time values L_i and the expected values μ_L should be weighted according to the amount of coil shipped Q_i, as shown in equation 4.3. Besides providing more impact on larger shipments, the performance of suppliers with frequent orders is prioritised over the ones with only sporadic deliveries.

$$\hat{\sigma}_L = \sqrt{\frac{\sum_{i=1}^{N} Q_i \cdot (L_i - \mu_L)^2}{\frac{(N-1)\cdot \sum_{i=1}^{N} Q_i}{N}}} \tag{4.3}$$

[1]The arrival date would cause misleading results as shipments from an intermediary warehouse are often delayed by the company

Until this moment, the company was only collecting data on the performance of the most important European supplier with an expected lead time of 8 and 16 weeks for standard and PET coils[2], respectively. The results shown in Table 4.1 were obtained with the available data and underline not only the high degree of variability of the delivery process, but also the disparity from the expected values of lead times. In fact, the standard deviation of standard coils is more than 20% of the average value. This analysis actually fostered the interest of the stakeholders, which are currently keen to ensure the gathering of information regarding the remaining suppliers.

Table 4.1: Example of the delivery performance for one specific supplier

Coil Standard	$\hat{\mu}_L = 9,1$ weeks	$\hat{\sigma}_L = 2,3$ weeks
Coil PET	$\hat{\mu}_L = 18,3$ weeks	$\hat{\sigma}_L = 3,9$ weeks

Demand

The expected value of the demand is estimated out of the average of the forecast demand over the protection period, which is equal to the considered lead time plus the review time. Thus, during the application of the replenishment policy within a chosen time frame, the safety stock level adapts according to the expected amount of future coil consumption. However, as the measures of variability and parameters are defined in advance, the safety stock coverage remains the same.

In the work of Zinn and Marmorstein (1990), the computation of safety stocks based on the variance of demand forecast errors attained the same service level with 15% less safety stock in comparison with the computation based on the variance of demand. Hence, we will use the forecast errors as a proxy to this approach in order to leverage the developed forecast method.

Although the methodology sets a weekly simulation of the production process to provide the most up-to-date data to the purchasing team, the forecast basis - sales rep forecast - is only updated in a monthly basis. Furthermore, it is not reasonable to calculate weekly forecast errors as that would require a huge amount of precision that cannot be achieved through the MRP replication. Nevertheless, the protection period is different from the forecast update interval for both cases.

Silver et al. (1998) present an empirical approximation (equation 4.4) to obtain the standard deviation of forecast errors $\hat{\sigma}_D$ over the protection period from the standard deviation over one forecast update period $\hat{\sigma}_1$. In this case, L is the number of basic forecast updates periods contained within the protection period (it does not need to be integer) and c represents an empirical coefficient set to $0,5$, as the authors demonstrated to be value that provides the best fit.

$$\hat{\sigma}_D = L^c \hat{\sigma}_1 \tag{4.4}$$

[2]Coated coil with higher processing time

4.3.2 Ordering Decisions

The main difference to be internalised within this procedure is the meaning of variable X, whose notation was previously introduced in chapter 2. While this variable represents the total demand in $L+\tau$ in Silver et al. (2009), it represents from now on the demand of a single week. Once again, this modification occurs from the purpose of the policy itself, which is to determine weekly requirements instead of final orders.

For that reason, despite using similar mathematical equations introduced in chapter 2, the calculation of both the reorder point s and order-up-to level S have now an entirely different meaning. The first covers the expected demand for the specific week for which is calculated plus the safety stock (equation 4.5), while the former adds to the reorder point the expected demand in a established number of weeks, according to the intended n (equation 4.6).

$$s = E(X) + SS \tag{4.5}$$

$$S = s + n \cdot \hat{\mu} - E(\tau) \cdot \hat{\mu} \tag{4.6}$$

At last, a requirement of coil is triggered whenever the sum of the stock on hand with the quantity ordered in backlog is below the reorder point. The backlog is considered within the stock level because it covers a significant amount of coil that is kept on purpose in an intermediary warehouse to reduce holding costs. Under such conditions, the raw materials can be shipped very fast to meet production requirements on time.

Following the triggering of a requirement, the net amount of coil of each week, N_w, is calculated through the difference between the order-up-to level S and the stock level, as shown in equation 4.7. As the methodology further guarantees the arrival of those requirements in due time because of restraints in the optimisation model showcased in the next subsection, the system moves to the following week considering that the company already received the requirements of the former week. When the procedure is completed sequentially for each week of the intended time frame, we attain all inputs required to perform optimisation, the last step of the approach.

$$N_W = S - Stock\text{-}on\text{-}hand - Backlog \tag{4.7}$$

4.4 Optimisation Model

The optimisation model concludes the devised approach to attain substantiated suggestions of purchasing orders, which will be further validated by the purchasing manager. Keeping in mind that the company was not interested in acquiring licensed software packages to support mathematical optimisation, the lack of capacity of free software to deal with such a big amount of decision variables and constraints prevented the formulation of a model that accounts all raw materials simultaneously. For this reason, and also on the account of both time restrictions and the company's acknowledged lack of analytical maturity to handle its multiple structures of contracts, the optimisation model will not integrate previously defined contract agreements with the suppliers.

Notwithstanding the mentioned limitations, the utilisation of OpenSolver®, the open source Excel add-in for optimisation, still allows the implementation of sophisticated models that can assimilate specific aspects of each supplier and achieve an optimal allocation of orders while maintaining an holistic integration provided by prior stages of the methodology. Since quantity discounts are not being offered based on the total business volumes, but rather on each individual order placed by the company, the existence of distinct runs for each coil does not prevent a realistic integration of discounts within the decision-making process. Moreover, restrictions in terms of order quantities are also imposed specifically for each reference, some of which are directly linked with the dimensions of the coil in question.

Firstly, all the different suppliers available $s \in \mathscr{S}$ are listed for each one of the coils employed by the company, alongside with the amount of net requirements N_w for each week $w \in \mathscr{W}$ in the predetermined time horizon, which are calculated through the methodology presented in section 4.3. At the same time, there is also the gathering of all the parameters related with supplier's conditions, such as prices and lot sizes.

The cornerstone of the model can be summarised in assuring the arrival of raw materials in time to avoid shortages in the production process. However, it is possible to identity requirements without enough time to fulfill the shipment from available suppliers, which makes the problem infeasible. Under such circumstances, we are left with two distinct options: satisfy the foreseen needs with an alternative coil or postpone the production and place an order to the fastest supplier. Given the complexity and the lack of data to conduct a reasoned resolution, the DSS takes care of providing visibility of these situations and waits for the experienced judgment of the purchasing team. Algorithm 1 summarises the activities performed under such conditions.

```
foreach coil do
    slack = minimum lead time in weeks − weeks until first requirement
    delay = Max{0; slack}
    if delay > 0 then
        aux = 0
        while aux < delay do
            aux = aux + 1
            waits for the decision of the purchasing team
            if substitutes coil then
                adds net requirements on the forecast of substitute coil
            else
                postpones requirements for the first permissible week
            end
        end
    end
end
```

Algorithm 1: Pseudocode for handling with foreseen shortages of coil

Whenever the purchasing team decides to conduct a substitution, the system converts automatically the quantities at stake by analysing the dimensions of both coils. Hence, the DSS will provide visibility of the evolution of expected waste, one of the crucial KPIs for the purchasing process.

As substitution processes trigger additional demand for alternative coils, the final step prior to the application of the model is the recalculation of weekly net requirements with an updated forecast. At last, the conditions are fulfilled to apply the model and achieve an optimal feasible solution for the scheduling and allocation of purchasing orders. The notation used is summarised in Table 4.2, that discloses the parameters incorporated in the problem.

Table 4.2: Table of notation for the optimisation model.

Sets and indices	
$s \in \mathscr{S}$	Suppliers
$w \in \mathscr{W}$	Weeks
$k \in \mathscr{K}$	Discount levels
Parameters	
N_w	Coil required on week w, in kilograms
P_s	Standard unitary price of supplier s, in euros
L_s	Lead time of supplier s, in weeks
B_s	Lot size of supplier s, in kilograms
M_s	Minimum order of supplier s, in number of lots
$D_{k,s}$	Percentage of discount of level k applied by supplier s
$I_{k,s}$	Minimum quantity required to benefit from a discount with level k applied by supplier s, in kilograms
C	Unitary weekly capital cost[a], in euros
A	Sufficiently large constant
n_w	Number of weeks covered
$n_{k,s}$	Number of price levels of supplier s
Decision Variables	
$Q_{s,w}$	Number of lots to be ordered to supplier s in week w
$X_{s,w}$	Binary variable that indicates whether there is an order to be placed to supplier s in week w
$Y_{k,s,w}$	Discount obtained (in euros) with level k to be applied by supplier s in week w
$Z_{k,s,w}$	Binary variable which takes the value 0 if the level k discount is applicable in week s; otherwise it takes the value 1
Auxiliary Variables	
$U_{s,w}$	Amount of coil to be delivered by supplier s in week w, in kilograms

[a] Average coil price multiplied by the established WACC

The main assumptions of the model are the following:

1. If a supplier does not impose a lot size, the lot size is set to 1 kilogram of coil.
2. The minimum order quantity is a multiple of the lot size.
3. The discount follows an all-unit policy.
4. The purchasing orders are considered to arrive on time, respecting each supplier delivery arrangement.

Altogether, four distinct sets of decisions variables can be found in the model, two of which are created to cope with the incorporation of discounts. The key variable is $Q_{s,w}$, as it represents the ultimate answer of the problem: the number of lots to order in each week for each supplier. On the other hand, $X_{s,w}$ is a binary variable that states whether there is a order placed to that supplier in a specific week. Finally, in terms of discounts, variable $Y_{k,s,w}$ discloses the discount obtained in euros and $Z_{k,s,w}$ determines whether there is a discount with level k to be applied.

- Formulation of objective function

  The objective function can be found in equation 4.8, where we aim to minimize overall costs that accounts for both carrying costs and acquisition costs (in which the potential obtained discounts should be deducted from the original amount). The former is defined by capital costs, which usually make up the majority of carrying costs (Silver et al., 2016) and whose calculation was conducted according to the company's weighted average cost of capital (WACC). The remaining carrying costs were neglected given the incapacity to translate risk and storage costs into reliable numbers. On the other hand, the absence of inbound logistic costs is motivated by the business reality of the company, in which the suppliers do not charge anything but actual price of the raw material. In fact, the suppliers protect themselves by imposing strong restrictions in terms of order quantities.

$$\text{Min} \sum_{s\in\mathscr{S}} \sum_{w\in\mathscr{W}} Q_{s,w} \cdot B_s \cdot P_s + \sum_{s\in\mathscr{S}} \sum^{w} U_{s,w} \cdot C \cdot (n_w - w) - \sum_{k\in\mathscr{K}} \sum_{s\in\mathscr{S}} \sum_{w\in\mathscr{W}} Y_{k,w,s} \tag{4.8}$$

- Formulation of constraints

  First set of constraints (auxiliary variable and demand)

  The auxiliary variable $U_{s,w}$ is introduced to enhance the readability of the model. In short, the model must have the visibility on each possible order arrival, which implies the incorporation of the lead times assured by the available suppliers. Thus, for each decision variable $Q_{s,w}$ there is an assigned auxiliary variable $U_{s,w}$ as shown in equation 4.9. Then, equation 4.10 imposes that the shipments of raw materials occur in due time, as the cumulative of arrivals should be at least equal to the cumulative of requirements in each week.

$$U_{s,w+L_s} = Q_{s,w} \cdot B_s \quad ,\forall s \in \mathscr{S}, \forall w \in \mathscr{W} \tag{4.9}$$

$$\sum^{w} N_w \leq \sum_{s\in\mathscr{S}} \sum^{w} U_{s,w} \quad ,\forall w \in \mathscr{W} \tag{4.10}$$

Second set of constraints (minimum order quantities)

Both equations 4.11 and 4.12 ensure that the problem is aligned with the reality in terms of minimum order quantities. The incorporation of lot size restrictions is also not forgotten, as the decision variable $Q_{s,w}$ is set to be an integer value, representing itself the number of lots to be ordered.

$$Q_{s,w} \leq X_{s,w} \cdot A \quad ,\forall s \in \mathscr{S}, w \in \mathscr{W} \tag{4.11}$$

$$X_{s,w} \cdot M_s \leq Q_{s,w} \quad ,\forall s \in \mathscr{S}, w \in \mathscr{W} \tag{4.12}$$

Third set of constraints (quantity discounts)

The incorporation of multiple levels of discount according with order quantities adds most of the complexity of the optimisation model. At first, the quantity of the discount must be limited according to the order quantity and each level discount percentage, as in equation 4.13. Afterwards, equation 4.14 is responsible for assigning the value 1 whenever the ordered quantity is inferior to the lower bound of the price interval, noted as $I_{k,s}$. Then, equation 4.15 further restricts the obtained discount, which will be equal to 0 whenever the decision variable $Z_{k,s,w}$ takes the value 1. At last, equation 4.16 is set to guarantee that only the most profitable discount level is selected, that is, the one with highest discount percentage.

$$Y_{k,s,w} \leq Q_{s,w} \cdot B_s \cdot P_s \cdot D_{k,s} \quad ,\forall k \in \mathscr{K}, \forall s \in \mathscr{S}, w \in \mathscr{W} \tag{4.13}$$

$$I_{k,s} - (Q_{s,w} \cdot B_s) \leq Z_{k,s,w} \cdot A \quad ,\forall k \in \mathscr{K}, \forall s \in \mathscr{S}, w \in \mathscr{W} \tag{4.14}$$

$$Y_{k,s,w} \leq (1 - Z_{k,s,w}) \cdot A \quad ,\forall k \in \mathscr{K}, \forall s \in \mathscr{S}, w \in \mathscr{W} \tag{4.15}$$

$$\sum_{k \in \mathscr{K}} Z_{k,s,w} \geq n_{k,s} - 1 \quad ,\forall s \in \mathscr{S}, w \in \mathscr{W} \tag{4.16}$$

4.5 The Decision Support System

Since the beginning of the project, the main deliverable is a Decision Support System to be used by the company, whose aim is to promote a holistic purchasing process of its main raw material. Besides suggesting purchasing orders, the tool is also devised to foster a continuous surveillance and increase the purchasing team focus on scenario analysis.

The first main challenge was the enormous amount of data that needs to be considered and that requires an extensive processing. As a significant portion of the data is only valuable for the MRP-based forecast, it was decided to incorporate that information directly into the Python® program responsible for that purpose. Afterwards, both the output of this process (that is, the forecast of coil consumption) and the remaining information is uploaded directly into the DSS, whose development was conducted in MS Excel®.

Requirements

In order to turn the devised methodology into a business application to be used by the purchasing team of the company, a mapping of the key requirements had to be drawn. The development of the tool in a software that the company already owned and which the end users would be familiarised with was one of the main concerns stated by the stakeholders. Therefore, despite losses in terms of running time performance, MS Excel® was the selected software to guarantee a work environment that the company is already acquainted.

Many functional requirements of the tool were iteratively drawn during the project. Its identification was promoted by frequent meetings with the purchasing team, in which they would require new features and assess the work developed so far. Some of the most important requirements are the following:

1. Develop tool in MS Excel®
2. Clean layouts and intuitive interfaces
3. Parameters outside company's ERP have to be changeable in the interface
4. Easy importation of the required data
5. Generate warnings to bullet proof the tool and foster surveillance
6. Clear outputs to ease a quick analysis and the subsequent validation process
7. Possibility to manually override the order suggestions while visualising its impact on the KPIs and contracts with the suppliers
8. Deployment of dashboards with the following information:
   (a) Evolution of forecast accuracy and historical coil consumption
   (b) Expected impacts of the validated purchasing orders on the KPIs
   (c) Status of the contracts with the company's suppliers
9. Export relevant collected data into condensed reports to be delivered to the administration of the company
10. Final purchasing orders should be loaded directly into the company ERP.

Architecture

The architecture of the decision support system is divided into four main elements, whose logic is comprised in Figure 4.3. Firstly, all the required information is integrated from two possible sources: other MS Excel® files and settings that occurs inside the tool itself. The Python® module is also represented in the first block to underline the incorporation of the results provided by the MRP replication, although this results are previously translated into an intermediary MS Excel®

file. Then, the DSS follows a logic of having an interface in which the end user can interact with the two built-in methodological modules: the replenishment algorithm and the optimisation model. The construction of the model is developed for each reference in VBA, ahead of the usage of OpenSolver®, that is represented in the third block of the figure. After the optimisation is finished, its outcome is analysed by the user, who is also entitled to perform modifications on the purchasing orders. At last, the main reports are exported in other MS Excel® files and the purchasing orders are uploaded directly into SAP®, the ERP software used by the company.

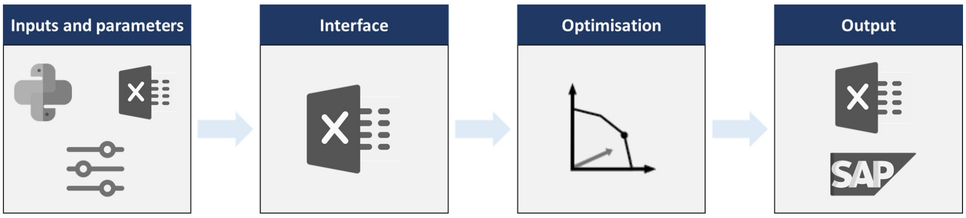


Figure 4.3: DSS Architecture

Interface

The applications starts with the homepage displayed in Figure 4.4. As it is possible to observe, it was decided to group five main sequential modules, ranging from the importation of inputs towards the exportation of purchasing orders and main reports. Some of the remaining interfaces are shown in Appendix C.

Figure 4.4: DSS Homepage

As seen in Figure C.1, the end user imports the required information through a specific and intuitive form. Afterwards, the parameters must be set according to the business reality and also the desired specifications of the purchasing team, as exemplified in the suppliers parameters interface represented in Figure C.2. It was decided to implement a feature that generates warnings at the end of the setting process, whose result can be seen in Figure C.3.

Then, by clicking the button to generate coil net requirements, the system automatically calculates both demand and supplier variability based on historical data, culminating in the implementation of the replenishment algorithm. When the algorithm is applied for the first time, the end user is led to the interface to deal with urgent coil requirements, as shown in Figure C.4. After deciding to postpone the requirements or substitute the missing coil, the algorithm is applied again automatically, generating the output seen in Figure C.5.

Now, the optimisation of purchasing can be made. After automatically running the model for each coil, its results will be outputted to the page that can be observed in Figure C.6. Then, the user has access to the validation interface depicted in Figure C.7, where it can alter the purchasing orders for each coil and observe its potential costs in comparison to the optimal solution provided by the Solver.

At last, the DSS allows to upload the final purchasing orders in the last module. Also at this point, the user can observe and export the required reports to get aware of the current situation of the company. Figure C.8 presents the outcome of one of the deployed reports.

Chapter 5

Results

The present chapter intends to show the results obtained from applying the described methodology to the metal packaging industry and to retrieve the major insights. Since the handover of the devised DSS occurred recently and the order-cycle time comprises at least 8 weeks, there is not enough data to measure the real impacts on key indicators for the company's stakeholders, thus, a comparison will be performed based on simulation with historical data.

In Section 5.1, the impacts on the forecast accuracy attained with the MRP replication are addressed. Then, the solution found for the assumption of a lead time for the definition of safety stocks is compiled in Section 5.2. Lastly, Section 5.3 presents the overall results achieved with the application of the replenishment policy and the optimisation model to create purchasing orders.

5.1 MRP-based forecast results

In order to assess whether the readjusted forecast process provides a better a head start to the overall purchasing process, several simulations of the manufacturing process were conducted in a monthly basis from April to December of 2019. As the system is fed with distinct sales rep forecasts and up-to-date inventory positions, the estimations of coil consumption for a specific month vary according to the timing of the simulation. Hence, in an effort to provide a better understanding of the actual effects of the devised methodology, the considered forecast for each month consists in the average value of the forecasts gathered from three distinct simulations, since two months in advance to the month itself. The same logic was applied to retrieve the forecast attained by the company at stake, such that a fair comparison is made.

Figure 5.1 illustrates the monthly variation of the Mean Absolute Percentage Error (MAPE) obtained from the implementation of the proposed methodology. As it is possible to observe, the devised forecast process results in an overall 4,2% reduction of forecast errors, despite not leading to positive outcomes throughout the whole period under analysis. The results achieved in both August and December demanded a further examination to prevent similar situations to occur in the future. The problem actually goes beyond these months and was identified together with the main stakeholders: the established order points are often ignored by the planning department, which generates underestimations of coil consumption.

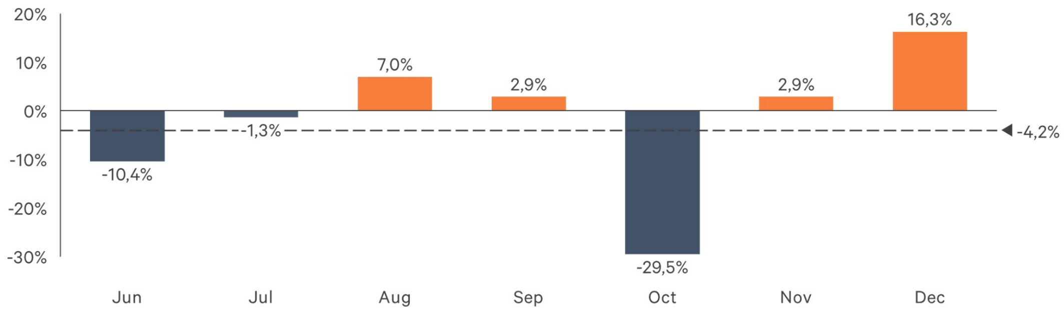


Figure 5.1: Difference of forecast errors (MAPE) between the devised approach and the AS-IS process

There are several reasons for this behaviour, such as the choice to anticipate demand on the pretext of capacity surplus (main motive behind December's gap) or production shifts due to employees vacations and scheduled preventive maintenance in some of the production lines. Either way, this situation required the creation of an auxiliary interface in which the planning department can update the items' parameters[1] for a specific time window in order to accommodate some sporadic decisions.

Notwithstanding these limitations, the simulation still originated a positive note, as there is confidence that with the appropriate validations from the process owners, the results will improve significantly. Moreover, the new interface intends to cut off situations such as the one witnessed in October, where the disregard of demand anticipations that happened in the previous two months led to an extreme overestimation of coil consumption. Therefore, this procedural change will also foster the alignment between the purchasing and planning departments, mitigating communication issues and ensuring a more complete exchange of information.

5.2 Scenario evaluation of lead times in safety stock computation

As mentioned in the previous section, it is vital to bear in mind that the information of the selected supplier is not available prior to the optimisation process. Thus, it is required to presume a value for the replenishment lead time in order to compute safety stock levels for each raw material. A simulation of the purchasing process of 2019 was conducted to perceive the impacts of lead time variations in the established KPIs. The three tested scenarios differ only on lead time assumptions, encompassing the usage of the minimum, average and maximum values.

A stabilisation period of two months was defined to ensure that the effects are analysed in a steady state. Under such assumption, it was possible to conclude that acquisitions costs do not vary significantly between scenarios, therefore this metric is not included in the present analysis. Table 5.1 summarises the results of all three scenarios at each existent *ABC-XYZ* quadrant, in which the

[1]The modifications can be performed item by item or to a whole format

selected heuristic appears highlighted in bold. The analysis was conducted in terms of the elected service level measure and weeks of stock coverage, where the latter is presented as the relative difference in comparison to the baseline scenario - "Minimum LT".

Table 5.1: Comparison of the service level and weeks of stock coverage for the tested scenarios

Quadrant	Minimum LT		Average LT		Maximum LT	
	Service Level	Stock	Service Level	Stock	Service Level	Stock
AX	**99,5%**	**-**	99,9%	+1,6	100%	+3,2
AY	97,4%	-	**98,8%**	**+1,8**	99,7%	+2,8
AZ	**100%**	**-**	100%	+3,1	100%	+6,5
BX	95,2%	-	**100%**	**+1,4**	100%	+1,9
BY	97,7%	**-**	**98,7%**	**+2,2**	99,9%	+5,6
BZ	97,0%	-	**97,0%**	**+2,4**	97,7%	+3,8
CY	**99,8%**	**-**	99,8%	+3,3	100%	+6,3
CZ	**98,1%**	**-**	98,1%	+2,9	98,8%	+4,8
Average	98,5%	-	99,2%	+2,2	99,5%	+3,9

Firstly, as the integration of waste in the definition of service level targets is yet to be completed, it is considered that A,B and C items are required to fulfill fill rates of 99%, 97,5% and 95%. The baseline scenario slightly fell short the targets for A and B items, which attained an average service level of 98,8% and 96,9%, respectively. On the other hand, the service level targets are met under the average lead time assumption, which allow us to discard the most drastic scenario, where the increases in terms of stock coverage clearly outweight the benefits of a higher service level.

In an attempt to balance carrying costs with shortage costs, it was decided to use the minimum lead time for coils that do not belong to AY and all B quadrants, that settled for a safer average lead time assumption. Despite the lack of benefits obtained for the BZ quadrant and the inherent increase of inventory levels, this choice seems reasonable considering that this simulation was fed with the company's positive biased forecast (see Figure 3.5) and the fact that shortages costs actually go beyond the cost of scrap from the substitute coil, due to hidden costs such as the handwork arising from the need to update the company's information systems.

At last, Figure 5.2 provides a sensitivity analysis of the assumption undertaken in each of the three examined scenarios in terms of inventory carrying costs, which are once again represented by capital costs. It is possible to conclude that the increase of safety stock levels prompted by more conservative lead time assumptions is considerable, motivating the choice to consider the minimum lead time whenever it seems to be viable. In fact, moving from this baseline assumption towards the remaining scenarios, "Average LT" and "Maximum LT", causes increases of 15% and 25% in capital annual costs, respectively.

When on-site results become available, it will be possible to complement this study with new insights deriving from wastage costs, culminating in a more comprehensive heuristic for the required lead time premise.

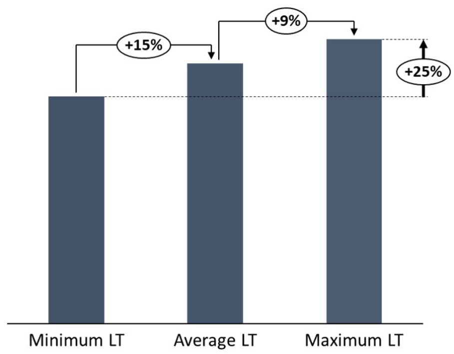


Figure 5.2: Comparison between carrying costs considering distinct lead times

5.3 Global Results

After the examination of singular aspects of the methodology, it is vital to provide a holistic view of the results when applying the devised approach from end-to-end. Nonetheless, as it is not possible to take advantage of the formulated strategy to tackle the previously identified challenges regarding the forecast process and the provided parameters are outdated relatively to the simulation period (April to December of 2019), this section presents the outcomes of the replenishment and optimisation methodological steps when provided with the company's original forecast.

The first key insights to withdraw comprise the impacts of both targeted service levels and demand variability measures in the computation of safety stocks, which can be observed in Figure 5.3. As it would be expected, the coverage values adapt according to each coil characteristics, such that the ones that are more volatile and unpredictable are provided with a higher amount of safety stock. Moreover, the shift caused by service level targets is also noticeable by observing the colors of the circles, given that for the same degree of demand variability, coils with higher service levels are placed further up the chart.

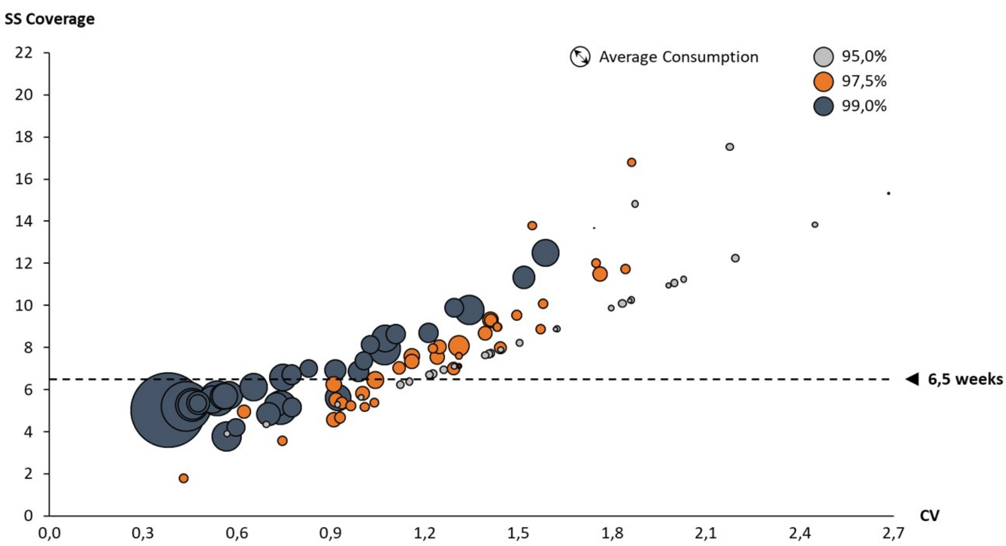


Figure 5.3: Analysis on safety stock definition

The relative size of the circles also allows to conclude that coils with higher demand volumes have usually lower variability, which counteracts the effect of the imposed rigorous service levels and prevents the carrying costs to escalate dangerously. Overall, the devised approach achieved an average safety stock coverage of 6,5 weeks.

Finally, Figure 5.4 shows the impacts on the devised KPIs by implementing the proposed methodology. The results lead to interesting conclusions: provided with the same forecast, both carrying costs and weeks of stock coverage would be reduced around 22%. While the carrying costs were calculated given the average price of each raw material, the stock coverage metric is used to provide an aggregated view of the amount of stock in comparison with the actual demand. The outcomes go in line with the expectations that the company fails to adjust its inventory levels towards the demand, leading to excessive stock build-ups to satisfy productive requirements. As for acquisition costs, a 3,8% decrease was found, which result in significant savings for the company given the larger scale of these values. Thus, preliminary results indicate a reduction of the sum of carrying and acquisition costs by 4,2% in the examined period, showing that gains can be obtained even with the same forecast process.

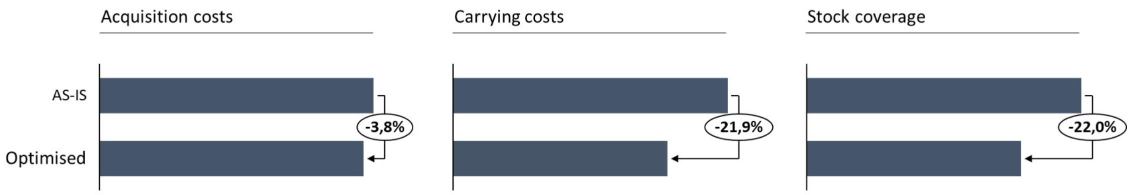


Figure 5.4: Comparison of the KPIs between the current and the proposed purchasing process

Since it is not possible to replicate the decision of the purchasing team when facing shortages of coil, the analysis of the attained service level is of utmost importance as a proxy to assess the impacts on the waste KPI. That said, Table 5.2 presents the fill rate that would be obtained for each *ABC* quadrant if the company was to follow the purchasing orders suggested by the optimisation model. As it is possible to observe, all the previously defined service level targets were met, which indicates that it is possible to reduce inventory levels without increasing the amount of waste nor compromising the company's delivery performance.

Table 5.2: Service level attained per ABC quadrant

Quadrant	Service Level
A	99,4%
B	98,5%
C	97,0%

A final remark should be done on how the proposed approach is expected to generate savings in spite of the incorporation of a slightly overestimated forecast of coil consumption, which can also account for the security margins obtained with respect to the targeted service levels. Given the reinforced expectation that the on-site implementation will converge to an unbiased forecast, the overall findings lead us to believe that the real impacts of the methodology can be broadened, resulting in more significant savings of costs incurred in the acquisition and management of raw materials.

Chapter 6

Conclusions and Future Research

This dissertation aimed to redefine the purchasing process of the main raw material of a metal packaging company in a holistic approach. The end goal was to propose a methodology intended to minimise total acquisition and carrying costs, without jeopardising the company's delivery performance and its ability to increase sales and consolidate its position in the market. In order to do so, a replenishment policy and an optimisation model were developed, that would then be implemented in a Decision Support System to create an enhanced scheduling of purchasing orders. The solution is based in the integration of each coil distinct sources of variability and all relevant suppliers' constraints, such that an optimal trade-off between acquisition and inventory costs is promoted. Another complementary goal was to provide a more robust forecast of coil consumption, capable of incorporating the inherent complexity of the shop floor and leverage available stock throughout the manufacturing process.

Notwithstanding the complex literature in inventory management and supplier selection, the amount of research that intertwines both fields is quite sparse and relies on several assumptions to relax some real-life constraints. Thus, it was required a tailor-made solution to accommodate company's specifications, that can ultimately contribute to bridge the literature gap between broad multi-supplier contexts and replenishment decisions in a manufacturing environment.

The modular nature of the devised approach allows to detach the forecasting process from the replenishment and allocation of purchasing orders, which turned out to be the core of the present work. In fact, the forecast module ought to be further validated due to the need to handle deviations between the provided parameters and the actual productive context. Nonetheless, the uncertainty measure designed to cope with the high error margin at the SKU level proofs to work as intended.

The pivotal proposed methodology extends a prestigious and well-suited replenishment policy found in literature, enabling the projection of the amount of net coil requirements in a selected time frame. The incorporation of these results in a developed mix-integer optimisation model allows to select the best supplier and timing of the purchase, such that productive requirements are met in due time and other key aspects such as quantity discounts are incorporated.

According to some experimental results, the application of this methodology is expected to generate savings of 4,2% in the company's total acquisition and carrying costs, without compromising service level targets. In particular, a significant decrease of 22% in weeks of stock coverage is a strong indicator of the presence of improving opportunities, corroborating with initial expectations of excessive inventory buildups. Moreover, an overall decrease of forecast errors was found, though at the expense of a pronounced underestimation of coil consumption, which should be overcome by the on-site validation of the provided parameters from the planning department. The fact that the methodology was able to extract measurable benefits in spite of the incorporation of the pre-existent overestimated forecast contributed to increase the expected potential of the project, demystifying the need for change amongst the company's stakeholders.

Since the implementation of the Decision Support System is already in motion, a second analysis should be performed to confirm the outcomes extracted from the preliminary results. Furthermore, it will be possible to assess the impacts of the methodology in terms of waste, which is the main motivation behind the incorporation of substitution amongst raw materials to define target service levels.

Despite the expected gains brought up by the present methodology, there are some limitations that could instigate further research. First, the forecast process could be made more reliable by incorporating sophisticated machine learning algorithms to the initial sales rep forecast. Future work might also proceed the efforts conducted to use historical data to attain more accurate productive lead times, rather than relying solely on standardised values.

As the optimisation model is applied individually for each coil, sourcing agreements are being currently neglected, which can ultimately trigger corrections from the purchasing team that do not correspond to the overall best strategy. A robust optimisation approach with penalty parameters for contract deviations could be one possible solution to overcome this constraint. Additionally, the usage of Gamma and Poisson distributions to model demand can mitigate errors arising from the undertaken normality assumption. At last, it would be beneficial to invest in an exhaustive quantification of inventory costs, enabling its implementation in the objective function of the model. Moreover, an ambitious vision of the future implies the collection of currently inaccessible data such as suppliers' quality standards, whose incorporation as additional criteria can be materialised in actual gains to the company.

As a closing remark, it is important to underline the relevance of the company's mindset shift. By providing an analytic-driven integrated view of the purchasing process and reducing the overall effort required to place insightful purchasing orders, the devised tool fosters an enhanced focus on scenario evaluation and continuous monitoring, which allows the company to more efficiently manage its raw materials inventory.

Bibliography

Aissaoui, N., Haouari, M., and Hassini, E. (2007). Supplier selection and order lot sizing modeling: A review. *Computers & operations research*, 34(12):3516–3540.

Arnold, J. R. T. (1998). *Introduction to materials management*. Prentice Hall, Upper Saddle River, N.J., 3rd edition.

Arıkan, E., Fichtinger, J., and Ries, J. M. (2014). Impact of transportation lead-time variability on the economic and environmental performance of inventory systems. *International Journal of Production Economics*, 157:279–288.

Berger, P. D., Gerstenfeld, A., and Zeng, A. Z. (2004). How many suppliers are best? a decision-analysis approach. *Omega*, 32(1):9–15.

Bijvank, M. and Vis, I. F. (2012). Lost-sales inventory systems with a service level criterion. *European Journal of Operational Research*, 220(3):610–618.

Bonser, J. S. and Wu, S. D. (2001). Procurement planning to maintain both short-term adaptiveness and long-term perspective. *Management Science*, 47(6):769–786.

Carter, J. R. and Yan, T. (2007). The procurement function's role in strategic outsourcing from a process perspective. *International Journal of Procurement Management*, 1(1-2):210–226.

Chaudhry, S. S., Forst, F. G., and Zydiak, J. L. (1991). A multicriteria approach to allocating order quantity among. *Production and Inventory Management Journal*, 32(3):82.

Chiang, C. (2002). Ordering policies for inventory systems with expediting. *Journal of the Operational Research Society*, 53(11):1291–1295.

Darr, W. (2020). *Fundamental Issues of Procurement Management*. tredition.

De Boer, L., Labro, E., and Morlacchi, P. (2001). A review of methods supporting supplier selection. *European journal of purchasing & supply management*, 7(2):75–89.

Destatis (2019). Kennzahlen der unternehmen des verarbeitenden gewerbes 2017. `https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Industrie-Verarbeitendes-Gewerbe/Tabellen/kennzahlen-verarbeitendes-gewerbe.html`.

Enns, S. T. (2002). Mrp performance effects due to forecast bias and demand uncertainty. *European Journal of Operational Research*, 138(1):87–102.

Fitzgerald, K. (2002). Best practices in procurement. *ASCET—Achieving Supply Chain Excellence through Technology*, 4.

Foerstl, K., Hartmann, E., Wynstra, F., and Moser, R. (2013). Cross-functional integration and functional coordination in purchasing and supply management. *International Journal of Operations & Production Management*.

Ghodsypour, S. H. and O'Brien, C. (1998). A decision support system for supplier selection using an integrated analytic hierarchy process and linear programming. *International journal of production economics*, 56:199–212.

Ghodsypour, S. H. and O'brien, C. (2001). The total cost of logistics in supplier selection, under conditions of multiple sourcing, multiple criteria and capacity constraint. *International journal of production economics*, 73(1):15–27.

Graves, S. C. (2011). *Uncertainty and production planning*, pages 83–101. Springer.

Guo, C. and Li, X. (2014). A multi-echelon inventory system with supplier selection and order allocation under stochastic demand. *International Journal of Production Economics*, 151:37–47.

Gupta, S. and Brennan, L. (1995). Mrp systems under supply and process uncertainty in an integrated shop floor control environment. *The International Journal of Production Research*, 33(1):205–220.

Hassanzadeh, A., Jafarian, A., and Amiri, M. (2014). Modeling and analysis of the causes of bullwhip effect in centralized and decentralized supply chain using response surface method. *Applied Mathematical Modelling*, 38(9-10):2353–2365.

He, X. X., Xu, S. H., Ord, J. K., and Hayya, J. C. (1998). An inventory model with order crossover. *Operations research*, 46(3-supplement-3):S112–S119.

Ho, C.-j. and Carter, P. (1996). An investigation of alternative dampening procedures to cope with mrp system nervousness. *International Journal of Production Research*, 34(1):137–156.

IndustryWeek and Kronos (2016). The future of manufacturing: 2020 and beyond. *IndustryWeek*.

Jacobs, F. R. and Chase, R. B. (2018). *Operations and supply chain management*. The McGraw-Hill Education series : operations and decision sciences. McGraw-Hill Education, New York, NY, fifteenth edition. edition.

Jayaraman, R., Roundy, R., and Srinivasan, R. (1994). Methods for parts procurement quantity determination where demand is uncertain for the product in which the parts are used.

Jayaraman, V., Srivastava, R., and Benton, W. (1999). Supplier selection and order quantity allocation: a comprehensive model. *Journal of Supply Chain Management*, 35(1):50–58.

Kang, H.-Y. and Lee, A. H. (2013). A stochastic lot-sizing model with multi-supplier and quantity discounts. *International Journal of Production Research*, 51(1):245–263.

Kodinariya, T. M. and Makwana, P. R. (2013). Review on determining number of cluster in k-means clustering. *International Journal*, 1(6):90–95.

Koh, S. C. L., Saad, S. M., and Jones, M. (2002). Uncertainty under mrp-planned manufacture: review and categorization. *International journal of production research*, 40(10):2399–2421.

Kotabe, M. and Murray, J. Y. (2004). Global sourcing strategy and sustainable competitive advantage. *Industrial marketing management*, 33(1):7–14.

Kruger, G. A. (1997). The supply chain approach to planning and procurement management. *Hewlett Packard Journal*, 48:28–33.

Lee, A. H., Kang, H.-Y., Lai, C.-M., and Hong, W.-Y. (2013). An integrated model for lot sizing with supplier selection and quantity discounts. *Applied Mathematical Modelling*, 37(7):4733–4746.

Li, Q. and Disney, S. M. (2017). Revisiting rescheduling: Mrp nervousness and the bullwhip effect. *International Journal of Production Research*, 55(7):1992–2012.

Lindgreen, A., Révész, B., Glynn, M., Costantino, N., Dotoli, M., Falagario, M., Fanti, M. P., and Iacobellis, G. (2009). A decision support system framework for purchasing management in supply chains. *Journal of Business & Industrial Marketing*.

MacQueen, J. et al. (1967). Some methods for classification and analysis of multivariate observations. In *Proceedings of the fifth Berkeley symposium on mathematical statistics and probability*, volume 1, pages 281–297. Oakland, CA, USA.

McDonald, S. C. (2009). *Materials management : an executive's supply chain guide*. John Wiley & Sons, Hoboken, N.J.

McKinsey&Company (2018). The route to no-touch planning: Taking the human error out of supply chain planning. `https://www.mckinsey.com/business-functions/operations/our-insights/the-route-to-no-touch-planning`.

Mendoza, A. and Ventura, J. A. (2012). Analytical models for supplier selection and order quantity allocation. *Applied Mathematical Modelling*, 36(8):3826–3835.

Minner, S. (2003). Multiple-supplier inventory models in supply chain management: A review. *International Journal of Production Economics*, 81:265–279.

Monczka, R. M. (2011). *Purchasing and supply chain management / Robert M. Monczka ... [et al.]*. South-Western, Australia ; Mason, OH, 5th edition.

Moynihan, G. P., Saxena, P., and Fonseca, D. J. (2006). Development of a decision support system for procurement operations. *International Journal of Logistics Systems and Management*, 2(1):1–18.

Muller, M. (2011). *Essentials of inventory management*. AMACOM, New York, 2nd edition.

Pazhani, S., Ventura, J. A., and Mendoza, A. (2016). A serial inventory system with supplier selection and order quantity allocation considering transportation costs. *Applied Mathematical Modelling*, 40(1):612–634.

Plenert, G. (1999). Focusing material requirements planning (mrp) towards performance. *European Journal of Operational Research*, 119(1):91–99.

Purohit, A. K., Choudhary, D., and Shankar, R. (2016). Inventory lot-sizing with supplier selection under non-stationary stochastic demand. *International Journal of Production Research*, 54(8):2459–2469.

Robinson, L. W., Bradley, J. R., and Thomas, L. J. (2001). Consequences of order crossover under order-up-to inventory policies. *Manufacturing & Service Operations Management*, 3(3):175–188.

Ronen, B. and Trietsch, D. (1988). A decision support system for purchasing management of large projects: Special focus article. *Operations Research*, 36(6):882–890.

Rosenblatt, M. J., Herer, Y. T., and Hefter, I. (1998). Note. an acquisition policy for a single item multi-supplier system. *Management Science*, 44(11-part-2):S96–S100.

Sarkis, J. and Talluri, S. (2002). A model for strategic supplier selection. *Journal of supply chain management*, 38(4):18–28.

Scheller-Wolf, A., Veeraraghavan, S., and van Houtum, G.-J. (2007). *Effective dual sourcing with a single index policy*. Citeseer.

Schuller, P. (2018). *A machine learning approach to promotional sales forecasting*. Master's dissertation, Faculdade de Engenharia da Universidade do Porto.

Silver, E. A., Naseraldin, H., and Bischak, D. P. (2009). Determining the reorder point and order-up-to-level in a periodic review system so as to achieve a desired fill rate and a desired average time between replenishments. *Journal of the Operational Research Society*, 60(9):1244–1253.

Silver, E. A., Pyke, D. F., and Thomas, D. J. (2016). *Inventory and production management in supply chains*. CRC Press.

Silver, E. A., Silver, E. A., Pyke, D. F., and Peterson, R. (1998). *Inventory management and production planning and scheduling*. Wiley, New York, 3rd edition.

Smits, S. (2003). *Tactical design of production-distribution networks: safety stocks, shipment consolidation and production planning.* Phd thesis, Eindhoven University of Technology.

Sousa, P. (2013). *Metodologias para Gestão de Inventário com Reposicionamento no Setor da Distribuição Farmacêutica*. Master's dissertation, Faculdade de Engenharia da Universidade do Porto.

Statistics, U. B. o. L. (2020). Producer price index by commodity for metals and metal products: Cold rolled steel sheet and strip. `https://fred.stlouisfed.org/series/WPU101707`.

Sun, J. and Van Mieghem, J. A. (2019). Robust dual sourcing inventory management: Optimality of capped dual index policies and smoothing. *Manufacturing & Service Operations Management*, 21(4):912–931.

Syntetos, A. A., Boylan, J. E., and Croston, J. (2005). On the categorization of demand patterns. *Journal of the operational research society*, 56(5):495–503.

Teunter, R. H., Babai, M. Z., and Syntetos, A. A. (2010). Abc classification: service levels and inventory costs. *Production and Operations Management*, 19(3):343–352.

Tunc, H., Kilic, O. A., Tarim, S. A., and Eksioglu, B. (2011). The cost of using stationary inventory policies when demand is non-stationary. *Omega*, 39(4):410–415.

Van Kampen, T. J., Van Donk, D. P., and Van Der Zee, D.-J. (2010). Safety stock or safety lead time: coping with unreliability in demand and supply. *International Journal of Production Research*, 48(24):7463–7481.

van Weele, A. (2009). *Purchasing and Supply Chain Management: Analysis, Strategy, Planning and Practice*. Cengage Learning.

Veeraraghavan, S. and Scheller-Wolf, A. (2008). Now or later: A simple policy for effective dual sourcing in capacitated systems. *Operations Research*, 56(4):850–864.

Weber, C. A. and Ellram, L. M. (1993). Supplier selection using multi-objective programming: a decision support system approach. *International Journal of Physical Distribution & Logistics Management*.

Whittemore, A. S. and Saunders, S. (1977). Optimal inventory under stochastic demand with two supply options. *SIAM Journal on Applied Mathematics*, 32(2):293–305.

Whybark, D. C. and Williams, J. G. (1976). Material requirements planning under uncertainty. *Decision sciences*, 7(4):595–606.

Yao, M. and Minner, S. (2017). Review of multi-supplier inventory models in supply chain management: An update. *Available at SSRN 2995134*.

Zhang, J.-l. and Zhang, M.-y. (2011). Supplier selection and purchase problem with fixed cost and constrained order quantities under stochastic demand. *International Journal of Production Economics*, 129(1):1–7.

Zhao, X., Lai, F., and Lee, T. (2001). Evaluation of safety stock methods in multilevel material requirements planning (mrp) systems. *Production Planning & Control*, 12(8):794–803.

Zinn, W. and Marmorstein, H. (1990). Comparing two alternative methods of determining safety stock levels: The demand and the forecast systems. *Journal of Business Logistics*, 11(1):95.

Appendix A

Complementary expressions for the (*R*,*s*,*S*) policy

A.1 Estimation of E(τ) and Var(τ)

Silver et al. (2009) models the inventory position of a system through a continuous time diffusion process, in which the time u for the diffusion process to reach s from S is given by equation A.1. Building on this premise, the authors obtain the density function of τ, presented in equation A.2.

$$f_u(u_0) = \frac{S-s}{\sigma\sqrt{2\pi u_0^3}}\exp\left[-\frac{(S-s-\mu u_0)^2}{2\sigma^2 u_0}\right], \quad 0 < u_0$$

$$f_\tau(\tau_0) = \frac{m}{CV\sqrt{2\pi}}\sum_{i=1}^{\infty}\frac{1}{\sqrt{(i-\tau_0)^3}}\exp\left[-\frac{(m+\tau_0-i)^2}{2(CV)^2(i-\tau_0)}\right], \quad 0 < \tau_0 < 1$$

Where:

$$m = \frac{S-s}{\mu} \tag{A.1}$$

Likewise the density function, the first two moments of the random variable τ depend only on two parameters: the distance $S-s$ and the measure of variability CV. As it was not possible to develop analytical expressions to obtain these moments, fractional polynomial functions were fit to adjust the moments of τ as a function of the coefficient of variation. The final expressions can be seen in equations A.4 to A.6, where the CV is noted as C and Φ and ϕ represent the cumulative and density functions of a unit normal variable, respectively.

$$E(\tau) = \frac{1}{2} + \frac{C^2}{2} - \frac{3}{4}C^4 + (\frac{1}{2} - C^2 + \frac{3}{2}CV^4)\Phi(-\frac{1}{C}) - (\frac{C}{2} - \frac{3CV^3}{2})\phi(-\frac{1}{C}) \tag{A.2}$$

$$E(\tau^2) = \frac{1}{3} + \frac{C^2}{2} - \frac{5C^6}{2} + (\frac{2}{3} - C^2 + 5C^6)\Phi(-\frac{1}{C}) + (-\frac{2C}{3} + \frac{5CV^3}{3} + 5C^5)\phi(-\frac{1}{C}) \tag{A.3}$$

$$Var(\tau) = E(\tau^2) - [E(\tau)]^2 \tag{A.4}$$

A.2 Rational approximation to find k

Given a unit normal loss function $G_u(k)$, there are several ways to compute an accurate approximation of the value k, that represents the safety factor in the context of the present project. The chosen procedure can be found in the work of Silver et al. (1998), consisting in the following rational approximation:

$$k = \frac{a_0 + a_1 z + a_2 z^2 + a_3 z^3}{b_0 + b_1 + b_2 z^2 + b_3 z^3 + b_4 z^4} \tag{A.5}$$

Where:

$z = \sqrt{\ln \dfrac{25}{G_u(k)^2}}$	$b_0 = 1$
$a_0 = -5.3925569$	$b_1 = -7.24964851 \times 10^{-1}$
$a_1 = 5.6211054$	$b_2 = -5.073266221 \times 10^{-1}$
$a_2 = -3.8836830$	$b_3 = 6.691368681 \times 10^{-2}$
$a_3 = 1.0897299$	$b_4 = -3.291291141 \times 10^{-3}$

Appendix B

Pseudocode of the MRP Simulation

Input: Item settings
Demand pulled from downstream links
Output: List of expected productions

```
foreach item do
    for w ← 1 to N_w do
        if first week then
            if Stock[1] < Order Point then
                StkIni_w = Stock
            else
                StkIni_w = Max{Stock − Uncertainty; OrderPoint}
            end
        else
            StkIni_w = StkEnd_{w−1}
        end
        Checks demand pulled from downstream links
        if StkIni_w − Demand_w < OrderPoint & Production is possible then
            Order_w = Max{(OrderPoint − ((StkIni_w − Demand_w)) × (1 + scrap); PrdMin}
            Entries_w = Order_w × 1/(1+scrap)
            PrevLinkDemand_{w−LeadTime} = Order_w × ConversionFactor
        end
        StkEnd_w = StkIni_w + Entries_w − Demand_w
    end
end
```

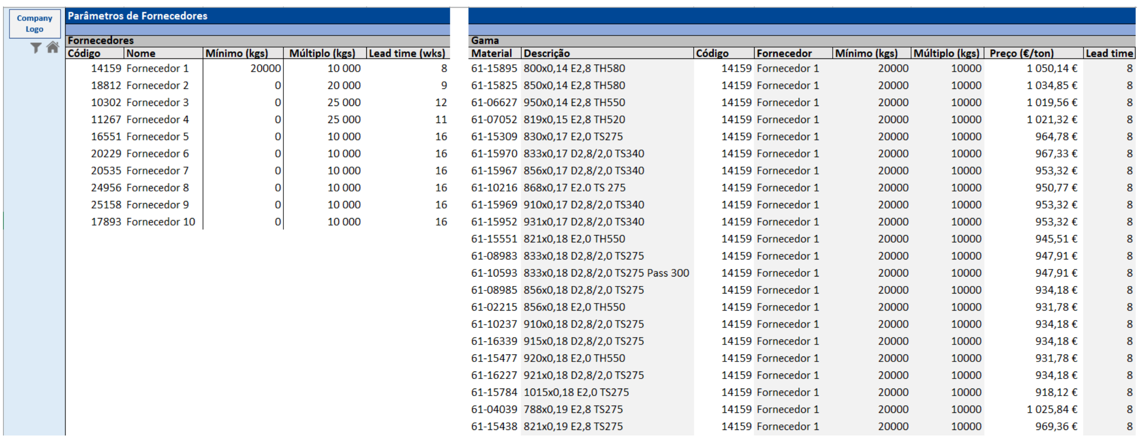
Algorithm 2: Pseudocode of the MRP Simulation

[1] Stock level retrieved from up-to-date inventory records

Appendix C

DSS Interfaces

Figure C.1: Importation Form



Company Logo

Parâmetros de Fornecedores

Fornecedores

Código	Nome	Mínimo (kgs)	Múltiplo (kgs)	Lead time (wks)
14159	Fornecedor 1	20000	10 000	8
18812	Fornecedor 2	0	20 000	9
10302	Fornecedor 3	0	25 000	12
11267	Fornecedor 4	0	25 000	11
16551	Fornecedor 5	0	10 000	16
20229	Fornecedor 6	0	10 000	16
20535	Fornecedor 7	0	10 000	16
24956	Fornecedor 8	0	10 000	16
25158	Fornecedor 9	0	10 000	16
17893	Fornecedor 10	0	10 000	16

Gama

Material	Descrição	Código	Fornecedor	Mínimo (kgs)	Múltiplo (kgs)	Preço (€/ton)	Lead time
61-15895	800x0,14 E2,8 TH580	14159	Fornecedor 1	20000	10000	1 050,14 €	8
61-15825	850x0,14 E2,8 TH580	14159	Fornecedor 1	20000	10000	1 034,85 €	8
61-06627	950x0,14 E2,8 TH550	14159	Fornecedor 1	20000	10000	1 019,56 €	8
61-07052	819x0,15 E2,8 TH520	14159	Fornecedor 1	20000	10000	1 021,32 €	8
61-15309	830x0,17 E2,0 TS275	14159	Fornecedor 1	20000	10000	964,78 €	8
61-15970	833x0,17 D2,8/2,0 TS340	14159	Fornecedor 1	20000	10000	967,33 €	8
61-15967	856x0,17 D2,8/2,0 TS340	14159	Fornecedor 1	20000	10000	953,32 €	8
61-10216	868x0,17 E2.0 TS 275	14159	Fornecedor 1	20000	10000	950,77 €	8
61-15969	910x0,17 D2,8/2,0 TS340	14159	Fornecedor 1	20000	10000	953,32 €	8
61-15952	931x0,17 D2,8/2,0 TS340	14159	Fornecedor 1	20000	10000	953,32 €	8
61-15551	821x0,18 E2,0 TH550	14159	Fornecedor 1	20000	10000	945,51 €	8
61-08983	833x0,18 D2,8/2,0 TS275	14159	Fornecedor 1	20000	10000	947,91 €	8
61-10593	833x0,18 D2,8/2,0 TS275 Pass 300	14159	Fornecedor 1	20000	10000	947,91 €	8
61-08985	856x0,18 D2,8/2,0 TS275	14159	Fornecedor 1	20000	10000	934,18 €	8
61-02215	856x0,18 E2,0 TH550	14159	Fornecedor 1	20000	10000	931,78 €	8
61-10237	910x0,18 D2,8/2,0 TS275	14159	Fornecedor 1	20000	10000	934,18 €	8
61-16339	915x0,18 D2,8/2,0 TS275	14159	Fornecedor 1	20000	10000	934,18 €	8
61-15477	920x0,18 E2,0 TH550	14159	Fornecedor 1	20000	10000	931,78 €	8
61-16227	921x0,18 D2,8/2,0 TS275	14159	Fornecedor 1	20000	10000	934,18 €	8
61-15784	1015x0,18 E2,0 TS275	14159	Fornecedor 1	20000	10000	918,12 €	8
61-04039	788x0,19 E2,8 TS275	14159	Fornecedor 1	20000	10000	1 025,84 €	8
61-15438	821x0,19 E2,8 TS275	14159	Fornecedor 1	20000	10000	969,36 €	8

Figure C.2: Suppliers' Parameters

Company Logo

Alertas

Folha	Alerta	Tipo	Material	Descrição
Consumos históricos	Os consumos históricos não estão atualizados. Último consumo: 23/12/2019	Erro		
Stock/Gama	Existem coils em gama sem stock em armazém	Aviso	61-03028	--Coil não definido na gama--
Stock/Gama	Existem coils em gama sem stock em armazém	Aviso	61-11433	--Coil não definido na gama--
Stock/Gama	Existem coils em gama sem stock em armazém	Aviso	61-11434	--Coil não definido na gama--
Stock/Gama	Existem coils em gama sem stock em armazém	Aviso	61-15968	--Coil não definido na gama--
Stock/Gama	Existem coils em gama sem stock em armazém	Aviso	61-16494	901x0,32 E2,0 TS275
Encomenda em aberto/Gama	Existem coils com pedidos de compra em aberto que não estão em gama	Erro	61-16500	--Coil não definido na gama--
Encomenda em aberto/Gama	Existem coils com pedidos de compra em aberto que não estão em gama	Erro	61-16563	--Coil não definido na gama--
Encomenda em aberto/Gama	Existem coils com pedidos de compra em aberto que não estão em gama	Erro	61-16602	837x0,32 E2,0 TS275
Encomenda em aberto/Gama	Existem coils com pedidos de compra em aberto que não estão em gama	Erro	61-16631	--Coil não definido na gama--

Figure C.3: Warnings sheet

Company Logo

Compras de Urgência

Validar Alterações

						Tomada de Decisão					
Coil	Descrição	Quantidade	Dt. Necessidade	Dt. Entrega	Atraso (wks)	Decisão	Substituto	Descrição	Desperdício	Qnt a Substituir	Alterado
61-02215	856x0,18 E2,0 TH550	15745	06/04/2020	25/05/2020	7	Atrasar necessidades			0	0	Sim
61-02215	856x0,18 E2,0 TH550	19625	20/04/2020	25/05/2020	5	Atrasar necessidades			0	0	Sim
61-02512	950x0,30 E2,0 TS275	1383	20/04/2020	25/05/2020	5	Substituir Coil	61-15900	1009x0,25 E2,8 TS275	86	1469	Sim
61-02512	950x0,30 E2,0 TS275	2264	04/05/2020	25/05/2020	3	Substituir Coil	61-15900	1009x0,25 E2,8 TS276	141	2405	Sim
61-02512	950x0,30 E2,0 TS275	2717	18/05/2020	25/05/2020	1	- Escolher opção -			0	0	Não
61-02545	771x0,34 E2,0 TS275	4715	20/04/2020	25/05/2020	5	- Escolher opção -			0	0	Não
61-06580	862x0,39 E2,0 TS275	28940	06/04/2020	25/05/2020	7	- Escolher opção -			0	0	Não
61-06580	862x0,39 E2,0 TS275	36253	20/04/2020	25/05/2020	5	- Escolher opção -			0	0	Não
61-06580	862x0,39 E2,0 TS275	37979	04/05/2020	25/05/2020	3	- Escolher opção -			0	0	Não
61-06580	862x0,39 E2,0 TS275	32782	18/05/2020	25/05/2020	1	- Escolher opção -			0	0	Não
61-06627	950x0,14 E2,8 TH550	20214	13/04/2020	25/05/2020	6	- Escolher opção -			0	0	Não
61-06627	950x0,14 E2,8 TH550	14646	20/04/2020	25/05/2020	5	- Escolher opção -			0	0	Não
61-06627	950x0,14 E2,8 TH550	36503	04/05/2020	25/05/2020	3	- Escolher opção -			0	0	Não
61-06627	950x0,14 E2,8 TH550	25554	11/05/2020	25/05/2020	2	- Escolher opção -			0	0	Não
61-07052	819x0,15 E2,8 TH520	31946	18/05/2020	25/05/2020	1	- Escolher opção -			0	0	Não
61-08983	833x0,18 D2,8/2,0 TS275	318478	30/03/2020	25/05/2020	8	- Escolher opção -			0	0	Não
61-08983	833x0,18 D2,8/2,0 TS275	162572	13/04/2020	25/05/2020	6	- Escolher opção -			0	0	Não

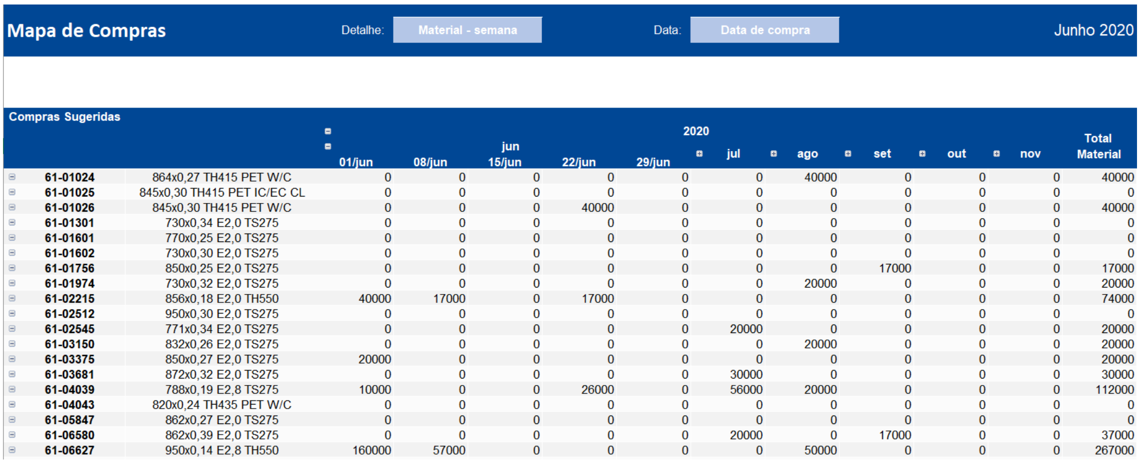
Figure C.4: Interface to handle urgent coil requirements

Company Logo

Necessidades de Coil

Material	Ano	Semana	Quantidade	LT Mínimo	Data Necessidade	Data Min Entrega	Tipo	Atraso
61-01024	2020	49	4652	16	30/11/2020	21/09/2020	Regular	0,00
61-01026	2020	42	2589	16	12/10/2020	21/09/2020	Regular	0,00
61-01026	2020	44	2644	16	26/10/2020	21/09/2020	Regular	0,00
61-01026	2020	45	2692	16	02/11/2020	21/09/2020	Regular	0,00
61-01026	2020	47	3478	16	16/11/2020	21/09/2020	Regular	0,00
61-01026	2020	48	1739	16	23/11/2020	21/09/2020	Regular	0,00
61-01756	2020	46	1642	8	09/11/2020	27/07/2020	Regular	0,00
61-01756	2020	47	3293	8	16/11/2020	27/07/2020	Regular	0,00
61-01756	2020	48	3293	8	23/11/2020	27/07/2020	Regular	0,00
61-01974	2020	42	3456	8	12/10/2020	27/07/2020	Regular	0,00
61-01974	2020	44	1895	8	26/10/2020	27/07/2020	Regular	0,00
61-01974	2020	46	2528	8	09/11/2020	27/07/2020	Regular	0,00
61-01974	2020	48	4110	8	23/11/2020	27/07/2020	Regular	0,00
61-01974	2020	49	3920	8	30/11/2020	27/07/2020	Regular	0,00
61-02215	2020	31	32980	8	27/07/2020	27/07/2020	Regular	0,00
61-02215	2020	33	18717	8	10/08/2020	27/07/2020	Regular	0,00
61-02215	2020	35	20313	8	24/08/2020	27/07/2020	Regular	0,00

Figure C.5: Output of replenishment algorithm - coil weekly net requirements



Mapa de Compras — Detalhe: Material - semana — Data: Data de compra — Junho 2020

Compras Sugeridas

		2020 jun 01/jun	08/jun	15/jun	22/jun	29/jun	jul	ago	set	out	nov	Total Material
61-01024	864x0,27 TH415 PET W/C	0	0	0	0	0	0	40000	0	0	0	40000
61-01025	845x0,30 TH415 PET IC/EC CL	0	0	0	0	0	0	0	0	0	0	0
61-01026	845x0,30 TH415 PET W/C	0	0	0	40000	0	0	0	0	0	0	40000
61-01301	730x0,34 E2,0 TS275	0	0	0	0	0	0	0	0	0	0	0
61-01601	770x0,25 E2,0 TS275	0	0	0	0	0	0	0	0	0	0	0
61-01602	730x0,30 E2,0 TS275	0	0	0	0	0	0	0	0	0	0	0
61-01756	850x0,25 E2,0 TS275	0	0	0	0	0	0	0	17000	0	0	17000
61-01974	730x0,32 E2,0 TS275	0	0	0	0	0	0	20000	0	0	0	20000
61-02215	856x0,18 E2,0 TH550	40000	17000	0	17000	0	0	0	0	0	0	74000
61-02512	950x0,30 E2,0 TS275	0	0	0	0	0	0	0	0	0	0	0
61-02545	771x0,34 E2,0 TS275	0	0	0	0	0	20000	0	0	0	0	20000
61-03150	832x0,26 E2,0 TS275	0	0	0	0	0	0	20000	0	0	0	20000
61-03375	850x0,27 E2,0 TS275	20000	0	0	0	0	0	0	0	0	0	20000
61-03681	872x0,32 E2,0 TS275	0	0	0	0	0	30000	0	0	0	0	30000
61-04039	788x0,19 E2,8 TS275	10000	0	0	26000	0	56000	20000	0	0	0	112000
61-04043	820x0,24 TH435 PET W/C	0	0	0	0	0	0	0	0	0	0	0
61-05847	862x0,27 E2,0 TS275	0	0	0	0	0	0	0	0	0	0	0
61-06580	862x0,39 E2,0 TS275	0	0	0	0	0	20000	0	17000	0	0	37000
61-06627	950x0,14 E2,8 TH550	160000	57000	0	0	0	0	50000	0	0	0	267000

Figure C.6: Scheduling of purchasing orders

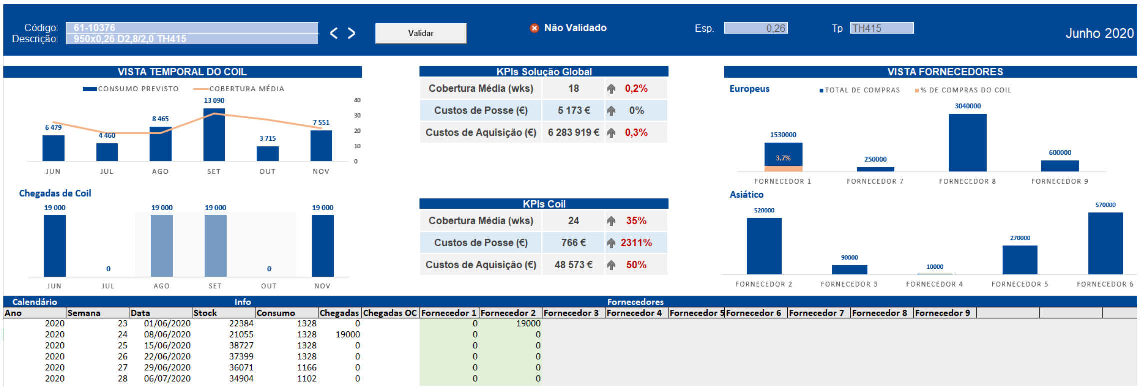


Figure C.7: Validation dashboard

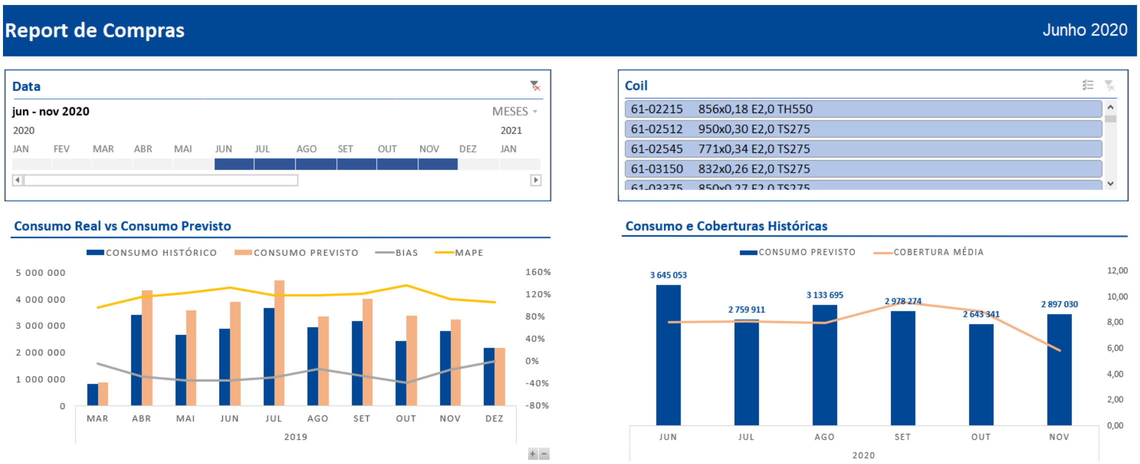


Figure C.8: Report